ISSN: 2249-7137 Vol. 15, Issue 5, May, 2025 SJIF 2022 = 8.252
A peer reviewed journal

ACADEMICIA
An International Multidisciplinary Research Journal

ISSN (online) : 2249 –7137

Editor-in-Chief : Dr. B.S. Rai

Impact Factor	:	SJIF 2022 = **8.252**
Frequency	:	Monthly
Country	:	India
Language	:	English
Start Year	:	2011

Indexed/ Abstracted : Scientific Journal Impact Factor (SJIF2022 - **8.252**), Google Scholar, CNKI Scholar, EBSCO Discovery, Summon (ProQuest), Primo and Primo Central, I2OR, ESJI, IIJIF, DRJI, Indian Science and ISRA-JIF and Global Impact Factor 2019 - 0.682

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A SMALL-SCALE SURVEY ON THE TEACHING AND LEARNING OF AO THROUGH NAGAMESE IN THE MULTILINGUAL CONTEXT OF MOKOKCHUNG

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DOI: 10.5958/2249-7137.2025.00026.6

ABSTRACT

This paper investigates the preference for Nagamese as the language of learning and classroom transaction by learners and teachers rather than a common indigenous language in Ao (a Naga tribal language) language classrooms in government primary schools in Mokokchung district of Nagaland. Nagamese is neither a state-recognised language nor a dominant indigenous language. However, in state government schools, where English is the official medium of instruction, non-Ao speaking children as well as teachers prefer Nagamese for classroom transactions. They also prefer to learn the Ao language through Nagamese, despite the fact that Nagamese does not share syntactic and grammatical features with Ao or any other indigenous Naga languages. The use of Nagamese for classroom transactions does not come under the purview of the NEP 2020's Three Language Formula, and is thus a pertinent subject of study within multilingual education.

KEYWORDS: *Ao, Multilingual Indigenous, Nagamese, NEP 2020.*

1. Introduction: Background of the study

In Nagaland, there is no common indigenous Naga language that can be recognised as the medium of instruction in school. Every tribe has its indigenous language with dialectal variations in several communities and thus, "[c]lassrooms comprise speakers of mutually unintelligible varieties such as Ao, Chang, Sangtam, Sumi, etc." Walling and Boruah (2024, p.281). The language of instruction in both private and government schools is English. However, in government schools, Nagamese is the language of choice and is used in classroom transactions primarily to bridge mutual-unintelligibility between teacher and learners, and among learners. In Mokokchung, Nagamese is not only the preferred language of classroom communication, it is also the medium of social communication among most learners. Most of these learners come to Mokokchung for education from linguistically and culturally diverse ethnic groups from far off and neighbouring rural areas. These non-Ao speaking children prefer to use Nagamese even when learning Ao in classrooms. This is important, because although Aos are the original residents of Mokokchung, Ao is still one of the minority languages of India, and faces endangerment.

Ao is one among the seventeen (17) Naga tribal communities which reside in Mokokchung district of northern Nagaland. The term Ao refers to both the tribe and their language. The Ao language has three dialects: Chungli, Mongsen and Changki. Among them, the Chungli dialect is usually used for formal communication and adopts the Roman script. The American Baptist missionaries first introduced the script to the Aos, when they brought modern education to Mokokchung in the early 1870s. Hence, Aos are considered as the pioneers among the Nagas in receiving formal education and are recognised as the most educated community in the state. As per 2011 census, Mokokchung records the highest literacy rate (91.62%) in Nagaland.

In Mokokchung district, Mokokchung Town is the locus of education, economy and public administration. Its municipal area includes 20 government schools comprising 4 primary, 12 middle and 4 high schools. According to the Unified District Information System for Education (UDISE+), 3047 children were enrolled in government schools under the municipal area of Mokokchung in 2022-23.

2. Statement of the Problem

Although the state government in Nagaland has recommended 17 Naga languages to be taught and learned as language subjects in the state school curriculum, not all the languages have yet been included in the curriculum. Classroom languages are determined by where the learners' school is located and the language of the local communities that is more widely used than other tribal languages. In Mokokchung, since the majority of the population are Aos, the government school syllabus includes only Ao as a language subject. However, over the years, people from various neighbouring tribal villages have begun to settle in Mokokchung for educational and other purposes. There are also children from far-flung areas who come to Mokokchung for education as this town is an education hub. For these non-Ao speakers, Nagamese is the preferred mode of communication with the local Ao and among one another. It has also come to be used in the Ao language classrooms for teachers' pedagogy as well as classroom communication. In this paper, we investigate the purposes for which Nagamese is used by teachers and students in the Ao language classroom, and their attitudes towards Nagamese as a preferred language of classroom transaction, especially for non-Ao learners. This is expected to shed light on the ways in which language education policies may be amended to include language practices in multilingual contexts where classrooms do not have a single dominant language of communication.

3. Literature Review and Research Gap

This section provides an overview of the main areas that relate to the use of indigenous languages in Indian classrooms. The main areas discussed include national language policy and mother tongue literacy, Mother Tongue-Based Multilingual Education (MTB-MLE), languages in the Nagaland education system and the use of Nagamese.

3.1 Indian government Policy Directives on Mother Tongue Literacy Development

The National Curriculum Framework (NCF) 2005 in Section 3.1.1 recommended that children's home language/mother tongue "[s]hould be the medium of learning in school… It is imperative that we honour the child's home language(s)" (p.37). In the same vein, Section 3.1d(iv) of the National Curriculum Framework for Foundational Stage (NCFFS) (2022) stated that a child's mother tongue/ home language does not only function as a medium of communication but is also associated with a child's personal and socio-cultural identity. The use of learners' mother tongues in education is a focus point in the National Education Policy (NEP) (2020), which stated, in Section 4.1.1 that the medium of instruction in learners' home language/mother tongue/local language/regional language should be implemented "wherever possible" (p. 13) at least till Class 5, and preferably till Class 8 and beyond. This is because "[y]oung children learn and grasp nontrivial concepts more quickly in their home language/mother tongue" (p.13). Section 3.2(a) of the NCFFS (2022) recommended that "[t]he primary medium of instruction would optimally be the child's home language/mother tongue/familiar language … in the Foundational Stage" (p.76). Furthermore, it suggested that in order to validate that "each child has continued proper use of their L1…at the Foundational Stage, it is essential to have Teachers (e.g., from the local community) who not only understand the language but also the local culture and traditions" (ibid). The NCFFS (2022), however, acknowledged that even though it is best to use learners' L1 while teaching, very often it is not feasible due to several reasons "[i]including the availability of Teachers who are proficient in the relevant languages." In such scenarios, it suggested that teachers use L1 as a support for "[a] child's transition to the new language, which is the language used for teaching, without losing out on their previous learning; for this the Teachers would have to be supported and encouraged to develop familiarity with the children's language." (p.76).

Although it is understood from the national education frameworks and policies that young children learn better in L1, accommodation of all learners' indigenous languages as the medium of instruction is a challenge for teachers in multilingual contexts such as Mokokchung. The sections below discuss the reasons behind this in more detail. In this connection, it is important to also look at how MTB-MLE is envisaged in the rest of India. The next section summarises multilingual education initiatives in states such as Andhra Pradesh, Assam, Chhattisgarh and Odisha which have implemented MTB-MLE.

3.2 Mother-Tongue-Based Multilingual Education in India (MTB-MLE)

Many schools in India have the potential of achieving early education through learners' mother tongue. Andhra Pradesh, Assam, Chhattisgarh and Odisha are the pioneering states that have adopted specific MTB-MLE programmes from early literacy stages, leading to systematic bridging to the other languages of education. Education in the mother tongue in the states of Andhra Pradesh and Odisha began early in the 2000s. In Andhra Pradesh 8 tribal languages were incorporated in education as medium of instruction while in Odisha MTB-MLE started with 10 tribal languages (Lepcha, 2023). Similarly, in Assam, at present there are 8 languages (Assamese, Boro, Bengali, Hindi, English, Garo, Hmar, Manipuri) adopted as medium of instruction at various grades at school. In addition, 15 languages are taught as language subjects in Assam schools. In Chhattisgarh, some materials on languages like Koya, Batri and Halbi have been developed under Sarva Shiksha Abhiyan (SSA) for implementation in school education. Various non-government organisations (NGOs) like the Amri Karbi Literature Committee etc. have also been promoting MTBMLE in communities (ibid).

However, even MTBMLE, which focuses on providing learners of all language communities an opportunity to begin education in their mother tongues, is unable to account for complex linguistic contexts such as Mokokchung, Nagaland where learners may not have a common indigenous language for classroom transactions. As Tupas (2015) argued, MTBMLE cannot be applied uniformly in all contexts, even in South Asia due to “inequalities of multilingualism” (p.112). The complexity of language use in Nagaland and its implications on education is discussed in the next section.

3.3Languages in Nagaland education system

In Nagaland, since classrooms include speakers of diverse Naga indigenous languages, English has been adopted as the medium of instruction in government schools. Additionally, the state government has included 17 Naga languages as language subjects to promote and preserve Nagaland’s linguistic and cultural heritage. However, it is a challenge to teach all the 17 local languages either due to shortage/absence of teachers who can speak all the indigenous languages or because of a higher number of teachers from a particular language community as against fewer teachers from other language communities. In Mokokchung, non-Ao learners from other Naga communities use Nagamese (the language of wider communication or LWC) even in Ao language classrooms. The state does offer Alternative English, Hindi or Bengali as a language subject for learners in lieu of Ao. However, since most of the government schools in Mokokchung offer only Alternative English, many learners from minority tribal language communities prefer to study Ao as they have little exposure to English.

3.4Role of Nagamese in Naga society

Nagamese began as a pidgin or a language of trade and commerce with the neighbouring state Assam but is today widely used as the medium of communication among the different Naga communities themselves for various social and economic purposes such as inter-tribal social gatherings and events, municipal announcements, business etc. Coupe (2022) described Nagamese as an “Assamese-based creoloid” that is extensively spoken among “speakers of mutually unintelligible languages” (p.13). Nagamese can thus be termed as a link language or a lingua franca. This language has a large influence of Assamese, with some lexical and syntactic features of Hindi and Bengali.

Nagamese is also spoken by non-Nagas such as the Marwaris, Nepalis, Biharis etc. who have settled in Nagaland for commercial and other purposes. This language has also begun to be popularly used in mass and social media. Several news channels in Nagamese have been recently launched. Various entertainment ventures such as films and music have also been produced in Nagamese. In fact, Nagamese has become prevalent not only in casual settings but even in formal settings such as education and administration (Aye, 2016).

Nagamese has now begun to be used as a first language among the younger generation born to inter-tribal married couples in Nagaland. Even children born to parents from one tribe but brought up in multilingual environments have begun to adopt Nagamese as their first language. From a linguistic perspective, Nagamese has now progressed from being used as an LWC to becoming a preferred home language of a new generation of Naga children.

These societal changes reflect corresponding developments in the school classroom. Nagamese is increasingly becoming the preferred language of classroom transactions as it is able to address issues of mutual unintelligibility. In many classrooms, it is the only language that connects both teachers to students and students from different tribes or language backgrounds.

Not much research on the use of Nagamese in education and language teaching in Nagaland was found during the literature review, nor did the researcher find any substantial work on multilingual Indian classrooms in Nagaland. This suggests that mother tongue based multilingual education in Nagaland has to be implemented through a deeper understanding of the contextual realities governing language learning in Nagaland.

4. Research Questions

The research questions that have guided this study are:

- What are some of the factors that mediate the use of Nagamese in the teaching and learning of Ao in primary classrooms at Mokokchung government schools?
- Do the teachers face any challenges in teaching Ao through Nagamese? If yes, what are the challenges and how do they tackle them?
- What are the beliefs and attitudes of teachers towards the use of Nagamese in the teaching - learning process of Ao in multilingual classrooms?
- What are the purposes of using Nagamese in the teaching and learning of Ao?

5. Objectives of the study

In this study, the researcher aimed to investigate Ao language classrooms in Mokokchung to better understand the use of Nagamese as a mediating classroom language. Through the study, the researcher aimed to:

- Ascertain the factors that determine the use of Nagamese at the primary level in the teaching-learning process of Ao in government schools in Mokokchung, Nagaland.
- Investigate whether Ao language teachers encounter any pedagogical challenges while teaching Ao and the kinds of strategies they implement in overcoming them.
- Understand teachers' opinions and attitudes towards the use of intermediary language-Nagamese, in the teaching and learning of Ao among multilingual learners.
- Study the objectives of using Nagamese in Ao language classroom transactions.

6. Methodology of the study

In this small-scale study, data was collected from teachers and learners of Ao in primary classes (between Classes 1 and 5) in government schools within the Mokokchung municipal area. 12 schools were selected to explore the use of Nagamese in the teaching and learning of Ao.The target group of this study comprised 59 learners from various communities between classes 1 and 5 and 12 Ao subject teachers (N=71). The data was collected through two instruments - a questionnaire for teachers and learners and classroom observation. The questionnaires were administered to one Ao subject teacher in each school while questionnaires to their learners were administered on the basis of the class composition i.e., one learner from each community. Classroom observations were carried out to substantiate the responses of the teachers and learners on classroom pedagogical practices. The duration of the observations was between 30 to 45 minutes depending on the school timetable.

The data was analysed through a mixed methods approach. The demographic information was quantified while classroom observation findings were analysed through thematic analysis. The sections below discuss the findings in detail.

7. Results and Findings

This section discusses the findings from the questionnaire responses of the Ao subject teachers and their learners and from the thematic classroom observations of the researchers.

7.1 Findings from the questionnaire

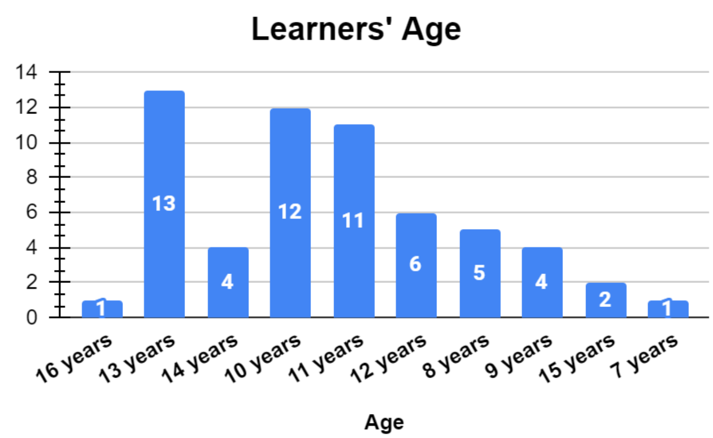
In this section we discuss the demographic profile of the study participants (teachers and learners), information on their classroom language use, and teachers' beliefs and attitudes. The tables below list the names of the schools where the study was conducted, the classes observed and the number of teachers and learners to whom the questionnaires were administered. 59 learners from 12 Ao-language classrooms were selected to participate in the questionnaire. The number of male students was 34 against 25 female students. Out of the 12 Ao subject teacher respondents, 8 were female and 4 were male. The minimum teaching experience of the teachers ranged between 11 to 15 years. The highest education qualification of the teachers was graduate whereas the lowest was senior secondary or 12th Class Pass. Most of the Ao subject teachers had D.El.Ed. Ed (Diploma in Elementary Education) as their additional qualification while others had B. Ed (Bachelor of Education), CPTE (Continuing Professional Teacher Education) and PSTE (Pre-Service Teacher Education).

TABLE 7.1 DEMOGRAPHIC DATA OF QUESTIONNAIRE RESPONDENTS

Sl. No	Name of the school	Class	No. of teacher respondents	Gender break up of teacher respondents		No. of learner respondents	Gender break up of learner respondents		Ao subject Teachers Age	Years of teaching experience	Educational Qualifications
				Male	Female		Male	Female			
1	GHS Sumi	Class 1	1		F	5	3	2	31-50 years	15 years & above = 10 teachers 11 to 15 years = 2 teachers	Graduate (7) 12th Class Pass (5) D.El.Ed.(3) B. Ed (2) CPTE (1) PSTE (1)
2	GMS Senkalemba	Class 2	1	M		8	5	3			
3	GMS Marepkong	Class 3	1		F	3	2	1			
4	GPS Mongsenbai	Class 3	1		F	3	1	2			
5	GMS Pongentola	Class 3	1	M		4	2	2			
6	GMS Artang	Class 3	1	M		7	4	3			
7	GPS Kichutip	Class 4	1		F	2	1	1			

8	GMS Kumlong	Class 4	1		F	5	2	3			
9	GMS Tongdentsüyong	Class 4	1	M		6	3	3			
10	GPS Lijaba Lijen	Class 5	1		F	4	3	1			
11	GMS Mokokchung Town	Class 5	1		F	5	4	1			
12	GMS A&B Sector	Class 5	1		F	7	4	3			
Total			12	3	8	59	34	25			

Fig 7.1 Learners' age profiles from questionnaire responses



7.1.1 Learners language backgrounds in Ao language classroom

Theteachers and learners' responses on indigenous languages spoken by learners in Ao language classrooms showed that the classrooms were richly multilingual. As many as 8 non-Ao Naga languages and 4 non-Naga languages were represented in the classes. According to the respondents, the highest number of non-Ao Naga children in the Ao language classroom belonged to Konyak and Khiamniungan tribes. Nepali children were the majority group among non-Naga language speaking communities. The full list of languages is given below:

1. **Non-Ao Naga indigenous languages spoken by learners:** Konyak, Khiamniungan, Chang, Sangtam, Phom, Yimkhiung, Lotha and Sumi/Sema
2. **Non-Naga languages spoken by learners:** Nepali, Hindi, Manipuri and Bhojpuri

7.1.2 Languages used for classroom transaction

This section briefly discusses the languages used by learners in the Ao language classroom with their peers and teachers. Table 7.1.2 shows the demographic break-up of the responses.

Language used with Peers: According to 9 teachers (75%) and 44 (74.5%) learners, learners spoke with their peers most frequently in Nagamese. Two main reasons were cited for this:

a) Many of these children neither spoke nor understood their friends' languages since everyone spoke a different indigenous language.

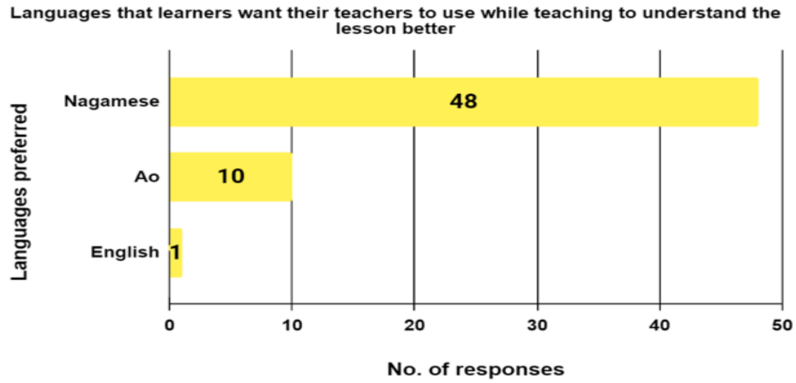
b) Every learner could communicate with their peers in Nagamese in the classroom.

Language used with teachers: The majority of the teachers and learners (61) reported that Nagamese was the preferred language used by children from non-Ao communities with teachers. Additionally, 48 out of 59 learners in the questionnaire preferred Nagamese as the language of teachers' classroom instruction.

Table 7.1.2 Language used with peers and teachers in Ao language classroom

Language used with peers in Ao language classroom			**Language used with teachers in Ao language classroom**		
Languages used by learners with peers	**No. of responses (teachers)**	**No. of responses (learners)**	**Languages used by learners with teachers**	**No. of responses (teachers)**	**No. of responses (learners)**
Nagamese	9	44	Nagamese	9	52
Nagamese and Ao	2	6			
Ao, Nagamese and English	1	0	Nagamese & Ao	3	2
Nagamese and Burmese	0	2			
Nagamese and Chang	0	1	Ao	0	4
Nagamese and Phom	0	1			
Nagamese and Hindi	0	1	English	0	1
Nagamese and Sema	0	1			
Ao	0	1		12	59
English	0	1			

Fig. 7.1.2 Languages preferred by students to learn Ao



7.1.3 Reasons for the use of Nagamese to teach/learn Ao

In the government schools of Mokokchung town in Nagaland, majority of the learners are from different non-Ao ethnic and linguistic minority groups who come to Mokokchung for education and speak mutually unintelligible languages. They are unable to follow teachers' instructions or the learning materials (textbooks etc.) in Ao. According to 10 out of 12 teachers (83%), Nagamese acts as an intermediary language while transacting Ao text contents. Two teachers, however, mentioned that they preferred to use Ao in the classroom because they are unable to find equivalent word meanings or vocabulary in Nagamese.

The table below lists the challenges in using Ao that necessitate the use of Nagamese, and the strategies used in teaching Ao.

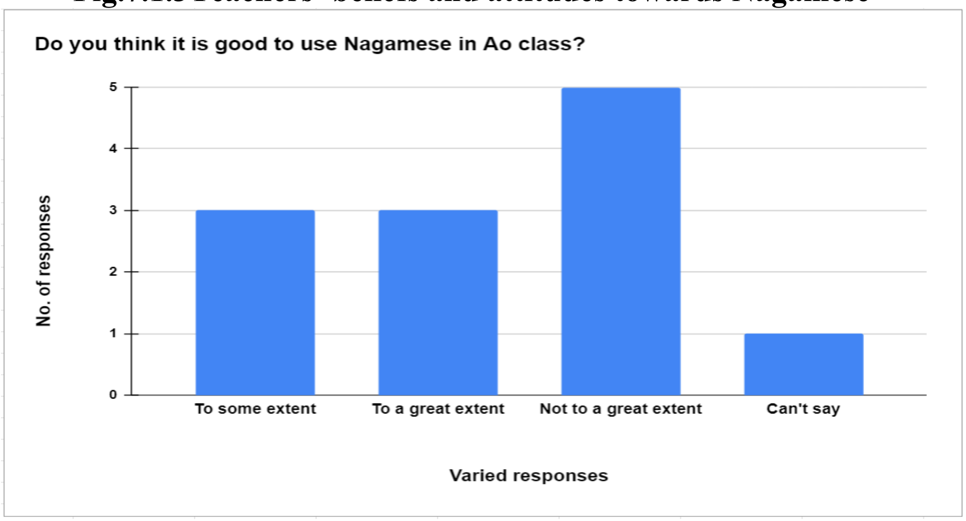
Table 7.1.3 Factors necessitating the use of Nagamese in Ao language classroom transactions

Challenges of teaching Ao to multilingual tribal children	**Preference for use of Nagamese**	**Ways of tackling the challenges**
1. Most learners belong to different non-Ao speaking tribal communities, do not understand Ao and remain unresponsive 2. Ao teachers' everyday language in both social and home domains was not Nagamese	1. Presence of learners from mutually unintelligible non-Ao and non-Naga languages	1. Providing meanings of Ao words in Nagamese 2. Translating and explaining the text content in Nagamese 3. Glossing, giving and illustrations 4. Mixing Nagamese and English while translating, explaining etc. 5. Using gestures and body movement while transacting the lesson 6. Using pictures from books

7.1.4 Beliefs and attitudes of teachers towards using Nagamese to teach Ao

Although 92% of the teachers mentioned challenges in using Ao and their preference for Nagamese to transact Ao lessons, their beliefs about using Ao in the teach-learning process contradicted their practices. For example, five teachers felt that Nagamese should not be used for content transactions. They believed that Ao should be taught and learned through the language itself as it would make "learning Ao easier" (Teacher C) and "to make them understand" (Teacher F). Teacher J felt that "Ao can be easily understood with more clarity if supplement(*sic*) with teaching aids." When asked what kind of supplementary materials in Nagamese should be provided to teach Ao, teachers mentioned charts, flashcards, pictures, and models. Thus, it can be observed from the data that most of the teachers faced a moral dilemma between their belief that a language is best taught through the language itself, and the linguistic and pedagogical challenges which force them to use Nagamese as a classroom language and also as a source of supplementary materials to teach Ao.

Fig.7.1.3Teachers' beliefs and attitudes towards Nagamese



7.2 Findings from classroom observation

Classroom observation was conducted to investigate in what ways Nagamese is used by Ao-language teachers in multilingual classrooms, and to determine the reasons for which both learners and teachers prefer to use Nagamese rather than Ao (the target language) or English (the official medium of instruction). In the sections below, findings of the study are coded and categorised thematically, with illustrations of the points as elicited from the data. The section also discusses other classroom practices that relate to and inform the language practices in the multilingual classrooms that were the site of the study. It was found that the observation data corroborated the questionnaire responses.

7.2.1 Purposes of using Nagamese in Ao class

Ao teachers were found to use Nagamese in classrooms for two main reasons:

(i) Content Transaction

The Ao language teachers used Nagamese as a bridge to transact the text content for three main purposes:

a. **Comprehension check:**

Since most of the learners were non-Ao speakers, teachers used comprehension questions to check background knowledge. For example, while taking a class on farming one Ao-language teacher asked the learners:

"*Yipru* tu janinanajani?"

[Do you know what a *storm* is?]

b. **Content explanation**:

The Ao subject teachers mostly explained the content in Nagamese. They read aloud the text either in sentences or paragraphs and explained/paraphrased/ translated the content in Nagamese. E.g., one teacher read aloud the chapter title and explained it in Nagamese:

"Moi khan aji lobolilaga tu khetiarumousamlaga ase"

[The lesson we are going to take today is about farming and climate]

c. **Explaining word meanings**:

Ao was a new language for most of the learners, so teachers provided meanings for unfamiliar words in Nagamese. E.g.,

"*Oshimane kotha*" *"Sükua tu kapra ki kua ase*"

[*Oshi* means language] [*Sü* means clothes]

d. **Taking feedback**:

During the lesson transactions teachers used Nagamese to take feedback from learners

"Moi kua tu honi nanahoni?" *"Kapra dulhake ki koi?"*

[Do you hear what I'm saying?] [What do you say for washing clothes?]

(ii) Instructions

Nagamese was used for both classroom instruction relating to the content and classroom management. The teachers instructed learners mostly in Nagamese while organising classwork and homework. For example, teachers provided direction to the learners while negotiating lessons, including which page to open and which lines to look at.

"Sob manu lesson 5 kulipi" *"Notun page kulipi"*

[All of you open lesson 5] [Turn to a new page]

7.2.2 Translanguaging strategies

The study also revealed that teachers used other languages and verbal strategies during classroom transactions. They used *translanguaging* strategies which allowed students to draw upon all their other languages while communicating in Nagamese. *Translanguaging* refers to "the deployment of a speaker's full linguistic repertoire without regard for watchful adherence to the socially and politically defined boundaries of named (and usually national and state) languages" (Otheguy, García and Reid, 2015, p.283). In other words, translanguaging allows students to use cognitive strategies from their known languages to comprehend new concepts by visualising, substituting words from one language in a text with another, discussing a classroom task in a familiar language but presenting it in the target classroom etc.

Data from survey and class observation showed that teachers used a mix of languages (Nagamese + Ao + English) for lesson explanation, translation, giving word meanings, checking learners' comprehension, demonstration, etc. While some teachers illustrated meanings from the Ao content through gestures to help in developing learners' comprehension, some used pictures. *Table 7.2* shows a list of translanguaging strategies used by the teachers, who were all Ao speakers:

Table 7.2.1 Teachers' translanguaging strategies

Using different languages	**Using pictures**	**Using gestures**
1. Nagamese e.g. *"sukhamati"* *"Aru amakandhan tu kimanlampapani tu lahiitu dak tu rakhibu"* 0. English e.g. *"Okay, look here" "Number two"* 0. Ao e.g. *"Asenoktemangyatelemsaaikalir"* 0. Nagamese + English e.g. *"Most important kaam tu khetikura tu ase koi ase"*	Drawing pictures on the blackboard, using pictures from book	Hands and body movement, nodding the head etc.

9.Conclusion and future scope of the research area

This study was conducted to examine the use of Nagamese as a medium of communication in the teaching and learning of Ao. The study found that Nagamese was used more than the target language in the development of learners' competence in Ao. It also revealed significant use of other languages in the teachers' pedagogy. Although most of the teachers agreed that it is better to use only Ao in the Ao-language class, they admitted that using Nagamese (and a mix of other languages) became inevitable since many students do not speak Ao and there is also mutual unintelligibility.

Mokokchung government schools demonstrate an intricate multilingual context where Nagamese and other languages are used regularly in teaching and learning of Ao. This issue requires special attention in formulating language policy and curriculum for education in Nagaland. With no official mandate to use Nagamese in classroom transactions, teachers are reluctant to admit to using it. It is difficult to ascertain to what extent Nagamese will have a bearing on the learning of Ao in Mokokchung classrooms unless more research is conducted.

This study concludes with the following thoughts:

- Development of pedagogical materials in Nagamese for Ao content transaction may be a useful resource for Ao language teachers in Mokokchung government schools
- Whether including Nagamese as a language in primary education may help learners of mutually unintelligible languages
- It may be necessary to revisit national education policies on children's right to education in their home language keeping in mind languages like Nagamese

As such, more research into the language strategies used in Ao primary classrooms would be required to address the complex and contested issues of endangerment of Ao if Nagamese continues to be used as a preferred mode of classroom transactions in multilingual classrooms.

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EMPIRICAL STUDY OF COST ACCOUNTING AND COSTING OF PRODUCTS IN GRAIN PROCESSING ENTERPRISES

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DOI:10.5958/2249-7137.2025.00027.2

ABSTRACT

This study examines the financial difficulties encountered in managing the cost of production of flour and compound feed products and cost calculation at grain processing enterprises. Based on the quantitative approach of empirical research, the main factors leading to the failure of the financial management of the cost of production of flour and compound feed products and cost calculation at grain processing enterprises are identified, the economic efficiency of the rules for the financial management of the cost of production per unit of flour and compound feed products and cost calculation is assessed through the developed scenarios, and the medium and long-term forecast indicators of the strategy for managing the cost of production per unit of flour and compound feed products and cost calculation are determined based on artificial intelligence technologies, in order to make scientifically based optimal decisions.

KEYWORDS: *Long-Term Forecast Indicators, Accounting For Production Costs, Financial Management Of Cost Calculations, Assessment Of The Effectiveness Of Production Costs,Collecting, Documenting, Processing Information,Making Optimal Decisions.*

1. INTRODUCTION

The issue of keeping track of expenses in the production of products of grain processing enterprises and improving the calculation of product costs is one of the urgent problems of scientific and research work. Cost accounting in product production and effective organization of product cost calculations require perfect control over the use of resources at any stage of technological processes and effective use of loss accounting information to achieve management goals.

In recent years, measures to improve the technological and organizational aspects of the activities of grain processing enterprises have had a significant impact on the structure of production costs and the cost of products, but the level of ensuring the economic efficiency of product production in the grain processing sector does not fully meet the established requirements.

Finding a solution to this problema complex organizational and management measures system, as well as various methods of collecting, documenting, processing and summarizing information on production costs and product costs, cost accounting and improving product calculations play an important role.

Practice shows that in recent yearsInsufficient attention is paid to improving the quality indicators of grain processing enterprises, identifying high levels of cost overruns and losses, and finding internal production resources. This situation leads to excessive costs in production and the loss of finished products. An objective description of the production process creates an opportunity for organizing and maintaining scientifically based accounting of costs and calculating the cost of products. This requires manufacturers to optimize the results of production activities at the enterprise [2; 97 - 113].

In a market economy, the adequacy and reliability of information on production costs and cost price is one of the ways to achieve competitive advantages in business management and administration. In practice, it is important to develop cost accounting and product cost calculation methods aimed at increasing the relevance of production activities, and to provide rules that determine the variety of methods that affect costs when making management decisions at various levels in the current system of accounting for production costs.

To date, the purpose of accounting for the cost of production and costing methods at grain processing enterprises and their application in the industry have not been fully covered in existing scientific works, or even generalized. The lack of methodological support for accounting helps to use existing methods in the theory and practice of accounting at grain processing enterprises and enrich them with techniques that correspond to the characteristics of the industry. However, issues related to improving cost accounting, as well as, the effectiveness of managing cost accounting and costing cannot be solved without the use of certain methods and approaches.

According to international practice, accounting for product production costs and costing helps to provide internal and external users with useful information on reducing product costs and effectively managing cost allocation. The information collected helps to ensure the economic stability of the enterprise and make effective management decisions.

So,product of the main goal of improving the methodology for accounting for production costs and costing is to increase production efficiency, find internal production resources to reduce costs, optimally use the internal potential of the enterprise, and achieve economic efficiency.

But today in enterprises product significant neglect of accounting of production costs and cost calculation, imperfect planning, violations of the rules of management organization cause certain deficiencies to occur. In particular, the volume of production of flour products and fine fodder at grain processing enterprises has significantly decreased, competition between enterprises has increased. This situation is causing disproportionality and monopolization of product prices, failure to pay for received products on time, increase in resource prices, and decrease in control efficiency. From this point of view, in grain processing enterprisesproductkeeping track of production costs and effective management of cost calculation, finding internal reserves of cost reduction, creating an opportunity to avoid bankruptcy processes of enterprises through the optimal distribution of costs, keeping track of production costs per unit of flour and soft feed products based on artificial intelligence technologies, and the long-term forecast indicators of the cost calculation management strategy for the long term are scientifically based optimal decision-making, quality production rate development of acceptable variants of determines the relevance of the topic of the article.

Literature Analysis

Economic scientists such as Kiseleva O.V., Makarova E.N., Kochetov V.L., Izykova A.V., Bondin I.A., and C. Drury conducted scientific research on the issues of accounting for production costs and improving cost calculation at processing plants. In particular, in the research of Bondin I.A., a concept of managing production costs at agricultural enterprises was created based on the systematization of the theory of production costs; the mechanism of production cost management was proposed to be targeted, informatized, resource exchange, and innovative methods, methods, and means of organizing and equipping agricultural production; factors affecting production costs with cost elements were identified; economic and statistical models of production costs at different levels of management were created; the impact of indicators characterizing the activities of enterprises on the cost of a unit of production was assessed; financial plans are drawn up that allow making management decisions aimed at reducing production costs; a methodical approach has been developed that provides for the expansion of the list of indicators used in practice (absolute liquidity ratio, debtor and creditor debt) to ensure the impartiality of the comprehensive assessment of the creditworthiness of enterprises; A mechanism for stratified distribution of budget funds was proposed through a comprehensive assessment of the creditworthiness of product manufacturers [3; 24].

*Kiseleva O.V. i*n his research, due to the lack of a unified approach in accounting, a method for accounting for production costs and cost calculation was developed; classifications of the method for accounting for production costs and cost calculation methods are proposed, the completeness of the identified features differs from other approaches; a new approach to cost accounting is determined by the characteristics of the enterprise's activities, a model for accounting for production costs was developed, in which the method for accounting for production costs and product cost calculation and the rules regulating them were formed [6; 24].

*Makarova E.N. i*n his research, taking into account the recommendations of international accounting and reporting standards and the specific features of accounting for production costs at processing enterprises, nomenclatures were determined for the items of unit cost of production; a scheme for operationally reflecting deviations of actual costs from standard costs at enterprises and methodological recommendations for their accounting were developed; a methodology for medium-term forecasting of production costs adapted to activity was recommended; a model for accounting and analytical support of the production cost management system at processing enterprises was developed by adapting the current accounting system to new economic conditions; a method for analyzing production costs based on the industry characteristics of enterprises was proposed, which allows optimizing the production costs of processing enterprises; the use of adaptive budgeting with a marginal approach in analyzing production costs was recommended; the effectiveness of accounting and analytical data in optimizing production costs was formed [7; 24].

*Kochetov V.L.*in the research of , a proposal was made to manage costs by profit centers, which would allow for the generalization and evaluation of data on costs and efficiency indicators for each center in flour industry enterprises; recommendations were developed to help align the cost control process for each participant in the production process with the organizational structure of the flour production complex, increase flexibility in decision-making, and increase the efficiency of the enterprise's activities in a competitive environment; a distribution by cost flows was proposed based on primary accounting documents; using structural analysis methods, the main sources of costs were summarized and systematized by cost items [5; 193-198].

*Izykova A.V. i*n his research, the structural elements of production costs were identified; production costs were studied as a general category of social reproduction; theoretical and methodological aspects of the formation of production costs and cost price were revealed; the differences between costs and cost price were identified and assessed through labor indicators; factors that significantly affect the cost price of products and production costs were identified and assessed; reserves for reducing the cost price of products were identified at enterprises and economic and mathematical models were created to optimize the production structure at the enterprise [4; 24].

However, in the above scientific works, based on the quantitative approach of empirical research, there have been no studies on identifying factors that lead to failures in the allocation of production costs of individual products and the calculation of product cost, evaluating the effectiveness of the optimal allocation of production costs of individual products and the calculation of product cost through developed scenarios, creating models for effectively assessing the accounting of product production costs and the calculation of cost at grain processing enterprises, and establishing scientifically based medium and long-term forecast indicators of the strategy for managing the accounting of production costs per unit of flour and compound feed products and the calculation of cost based on artificial intelligence technologies.

1. Methodology

It should be noted that the intensive growth of production volumes at grain processing enterprises is ensured by the accounting of production costs and the influence of factors affecting the cost of production. This situation requires the scientific substantiation of the accounting of production costs and cost calculation. Our goal is to increase the efficiency of grain processing enterprises, improve the methodology of accounting for production costs and cost calculation, find internal resources for reducing costs, create opportunities for enterprises to avoid bankruptcy processes through optimal distribution of costs, and provide high-quality**production rate.** It consists of developing acceptable options for and generalizing and holistically systematizing the elements associated with them.

Currently, there are no models for effectively estimating the cost of production and calculating the cost of grain processing enterprises. Therefore, in order to mathematically characterize the composition of the cost of production and calculating the cost of production, it is necessary to pay serious attention to the quantitative and qualitative indicators that represent them. In accordance with the conditions for mathematically characterizing the cost of production and calculating the cost of production processes at grain processing enterprises, we have developed models and algorithms for calculating the cost of production and calculating the cost of production of flour products and compound feed.

I. Algorithms for keeping accounts of production costs of flour products and calculating product costs in grain processing enterprises were developed in the following order:

1. The unit of initial wholesale value of grain (D_{uq}^{e})is equal to the ratio of the quantity of grain consumed for the production of flour products(D_{dm})multiplied by the wholesale price of grain (b_{du})to the number of flour products produced (M_{um})

$D_{uq}^{e} = (D_{dm} * b_{du}) : M_{um}$

2. The total wholesale unit cost of grain (D_{tq}^{e}) (including transportation costs) is equal to the ratio of the total wholesale cost of grain (D_{uq}^{e}), railway costs (X_{ty}), automobile costs (X_{av}), internal transportation costs (X_{it}) and savings interest (X_{jf}) spent on the production of flour products to the total flour products produced (M_{um}).

$D_{tq}^{e} = D_{uq}^{e} + (X_{ty} + X_{av} + X_{it} + X_{jf}) : M_{um}$

3. Unit of value of additional products (M_{qq}^{e})bran product (M_{kp})with wheat waste (M_{bc}) is equal to the ratio of the sum of the values of flour products produced (M_{um})

$M_{qq}^{e}= (M_{kp} + M_{bc}) : M_{um}$

4. The total unit value of grain after deducting the cost of ancillary products (D_{yq}^{e}) is equal to the difference between the unit value of grain (D_{tq}^{e}) plus transportation costs and the cost of ancillary products (M_{qq}^{e}).

$D_{yq}^{e}= D_{tq}^{e} - M_{qq}^{e}$

5. The unit cost (X_{mp}^e) paid to suppliers and contractors is equal to the ratio of the sum of electricity consumption (S_{ee}), water consumption (S_{sr}), gas consumption (S_{gz}) and other resource consumption (S_{br}) to the amount of flour produced (M_{um}).

$X_{mp}^e = (S_{ee} + S_{sr} + S_{gz} + S_{br}) : M_{um}$

6. The unit cost of various other materials used to produce a product (S_{bm}^e) is equal to the ratio of the sum of the cost of yarn (S_{ip}), labels (S_{ek}), bags (S_{qp}) and other materials (S_{tm}) to the number of flour products produced (M_{um})

$S_{bm}^e = (S_{ip} + S_{ek} + S_{qp} + S_{tm}) : M_{um}$

7. Direct and indirect unit costs (X_{bb}^e) are equal to the ratio of the sum of fuel (S_{yq}), spare parts (S_{eq}), construction materials (S_{qm}), various other materials (S_{bm}), expenses paid to suppliers and contractors (S_{mb}), wages (S_{is}), single social payment (S_{it}), depreciation of fixed assets (S_{am}) and other expenses (S_{bs}) to the total amount of flour produced (M_{um}).

$X_{bb}^e = (S_{yq} + S_{eq} + S_{qm} + S_{bm} + S_{mb} + S_{is} + S_{it} + S_{am} + S_{bs}) : M_{um}$

8. The unit cost of production (T_{is}^e) is equal to the sum of the unit cost of grain (D_{yq}^e), the ratio of the value of grain lost during transportation, storage and production (Q_{yb}) to the flour products produced (M_{um}), and the sum of the unit direct and indirect costs (X_{bb}^e)

$T_{is}^e = (D_{yq}^e + Q_{yb}) : M_{um} + X_{bb}^e$

9. Other operating expenses (X_{bo}^e) are equal to the ratio of the sum of land tax (SQ_{er}), water tax (SQ_{sv}), property tax (SQ_{ms}), other types of taxes (SQ_{bt}) and other types of expenses (X_{bt}) to the total flour products produced (M_{um}).

$X_{bo}^e = (SQ_{er} + SQ_{ms} + SQ_{bt} + X_{bt}) : M_{um}$

10. The unit cost of production (X_{dr}^e) is equal to the ratio of the sum of administrative and management costs (X_{mb}), selling costs (X_{rl}) and other operating costs (X_{bo}) to the total flour products produced (M_{um}).

$X_{dr}^e = (X_{mb} + X_{rl} + X_{bo}) : M_{um}$

11. Total unit production costs (X_{um}^e), unit production cost (T_{is}^e), unit period costs (X_{dr}^e) and the ratio of financial activity costs (X_{mf}) to flour products produced (M_{um}) is equal to the sum of

$X_{um}^e = T_{is}^e + X_{dr}^e + (X_{mf} : M_{um})$

12. The unit of gross profit (F_{ux}^e) is equal to the unit of the difference between the unit of wholesale price of the product (Q_{ss}^e) (excluding value-added tax) and the unit of total costs (X_{um}^e).

$F_{ux}^e = Q_{ss}^e - X_{um}^e$

13. Profit tax (S_{fs}^e) is equal to the ratio of profit before tax (F_{ts}) multiplied by the profit tax rate (F_{ts}) to the amount of flour produced (M_{um}).

$S_{fs}^e = (F_{ts} * F_{ss}) : M_{um}$

14. Value Added Tax (Q_{qs}) is equal to the product sold (M_{rq}) multiplied by the tax rate (S_{qs})

$Q_{qs} = M_{rq} * S_{qs} / (S_{qs} + 100)$

15. The unit of the wholesale selling price of the product (including VAT) (Q_{uq}^e) is the wholesale price of the product (Q_{ss}) (excluding VAT) plus VAT (Q_{qs}) is equal to the ratio of the difference in flour products produced (M_{um})

$Q_{uq}^e = (Q_{ss} - Q_{qs}) : M_{um}$

16. Net profit unit (F_{sf}^e)equal to the ratio of the difference between the unit of profit of general economic activity (F_{ux}^e) and the profit before tax (F_{ts}) to the number of flour products produced (M_{um})

$F_{sf}^{e} = F_{ux}^{e} - F_{ts}: M_{um}$

17. Rate of return:

17.1. The level of profitability relative to the cost of production (R_{ut}) is expressed as the ratio of the net profit unit (F_{sf}^{e}) to the cost of production unit (T_{is}^{e}):

$R_{ut} = F_{sf}^{e} * 100 / T_{is}^{e}$

17.2 The level of profitability (R_{ix}) relative to total costs is expressed as the ratio of net profit (F_{sf}^{e}) to total costs (X_{um}^{e}):

$R_{ix} = F_{sf}^{e} * 100 / X_{um}^{e}$

18. Accounting and cost calculation of production costs of flour products
conditions are expressed in the form of the following inequalities:

$D_{uq}^{e} < D_{tq}^{e}$; $M_{qq}^{e} < D_{tq}^{e}$; $T_{is}^{e} > X_{be}^{e}$; $X_{um}^{e} > T_{is}^{e}$; $F_{sf}^{e} < F_{ux}^{e}$

II.Algorithms for keeping track of the costs of production of fodder products in grain processing enterprises and calculating the cost of products were developed in the following order:

1. Unit of total cost of raw materials (Q_{xa}^{e}) bran (X_{kp}), chaff (X_{tr}), corn grain (X_{md}), flour (X_{un}), barley (X_{ar}), wheat waste (70 – 85%) (X_{ch}), wheat waste (50 – 70%) (X_{sh}), lime flour (X_{ou}) and mechanical losses (X_{my}) are equal to the ratio of the sum of the prices of each of them to the produced compound feed products (M_{oe})

$Q_{xa}^{e} = (X_{kp} * b_{kp} + X_{tr} * b_{tr} + X_{md} * b_{md} + X_{un} * b_{un} + X_{ar} * b_{ar} + X_{ch} * b_{ch} + \quad + X_{sh} * b_{sh} + X_{ou} * b_{ou} + X_{my}) : M_{oe} * b_{my}$

where b_{kp}, b_{tr}, b_{md}, b_{un}, b_{ar}, b_{ch}, b_{sh}, b_{ou}, b_{my} are the prices of raw materials

2. The unit cost of production (T_{ic}^{e}) is the total cost of raw materials (Q_{xa}^{e}) is equal to the ratio of the sum of auxiliary materials (S_{ym}), electricity consumption (S_{ee}), railway costs (X_{ty}), car costs (X_{av}), internal transportation costs (X_{it}), spare parts (S_{eq}), wages (S_{is}), single social payment (S_{it}), depreciation of fixed assets (S_{am}), equipment maintenance costs (X_{us}) and other costs (S_{bs}) to the produced compound feed products (M_{oe})

$T_{ic}^{e} = Q_{xa}^{e} + (S_{ym} + S_{ee} + X_{ty} + X_{av} + X_{it} + S_{eq} + S_{is} + S_{it} + S_{am} + X_{us} + S_{bs}) : M_{oe}$

3. Other operating expenses unit (X_{bo}^{e}) is equal to the ratio of the sum of land tax (SQ_{er}), water tax (SQ_{sv}), property tax (SQ_{ms}), other types of taxes (SQ_{bt}) and other types of expenses (X_{bt}) to the total amount of compound feed produced (M_{oe}).

$X_{bo}^{e} = (SQ_{er} + SQ_{ms} + SQ_{bt} + X_{bt}) : M_{oe}$

4. The unit cost of the period (X_{dr}^{e}) is equal to the ratio of the sum of administrative and management costs (X_{mb}), selling costs (X_{rl}) and other operating costs (X_{bo}) to the total amount of compound feed produced (M_{oe}).

$X_{dr}^{e} = (X_{mb} + X_{rl} + X_{bo}) : M_{oe}$

5. Total unit production costs (X_{um}^{e}), unit production cost (T_{is}^{e}), unit period costs (X_{dr}^{e}) and the ratio of financial activity costs (X_{mf}) to the total feed produced (M_{oe}) is equal to the sum of

$X_{um}^{e} = T_{is}^{e} + X_{dr}^{e} + (X_{mf} : M_{oe})$

6. The unit of gross profit (F_{ux}^{e}) is equal to the unit of the difference between the unit of wholesale price of the product (Q_{ss}^{e}) (excluding value-added tax) and the unit of total costs (X_{oe}^{e}).

$F_{ux}^{e} = Q_{ss}^{e} – X_{oe}^{e}$

7. Profit tax (S_{fs}^{e}) is equal to the ratio of profit before tax (F_{ts}) multiplied by the profit tax rate (F_{ss}) to the flour products produced (M_{oe})

$S_{fs}^{e} = (F_{ts} * F_{ss}): M_{oe}$

8. Value Added Tax (Q_{qs}) is equal to the product sold (M_{rq}) multiplied by the tax rate (S_{qs})
$Q_{qs} = M_{rq} * S_{qs} / (S_{qs} + 100)$

9. The unit of the wholesale selling price of the product (including VAT) (Q_{uq}^{e}) is the wholesale price of the product (Q_{ss}) (excluding VAT) plus VAT (Q_{qs}) is equal to the ratio of the difference in the produced compound feed products (M_{oe})
$Q_{uq}^{e} = (Q_{ss} - Q_{qs}) : M_{oe}$

10. Net profit unit ((F_{sf}^{e})equal to the ratio of the difference between the unit profit of the general economic activity (F_{ux}^{e}) and the profit before tax (F_{ts}) to the amount of compound feed produced (M_{oe})
$F_{sf}^{e} = F_{ux}^{e} - F_{ts}: M_{oe}$

11. Rate of return:
11.1. The level of profitability relative to the cost of production (R_{ut}) is expressed as the ratio of the net profit unit (F_{sf}^{e}) to the cost of production unit:
$R_{ut} = F_{sf}^{e} * 100 / T_{is}^{e}$
11.2. The level of profitability (R_{ix}) relative to total costs is expressed as the ratio of net profit (F_{sf}^{e}) to total costs (X_{oe}^{e}):
$R_{ix} = F_{sf}^{e} * 100 / X_{oe}^{e}$

12. The conditions for accounting and cost calculation of production costs for dry fodder products are expressed in the form of the following inequalities:
$T_{is}^{e} > X_{be}^{e}$; $X_{oe}^{e} > T_{is}^{e}$; $F_{sf}^{e} < F_{ux}^{e}$

Thus, these models and algorithms allow us to use them as a rule for calculating the cost of production and expressing the cost calculation for a certain period (month, quarter, year). Their typical conditions are summarized and systematized, taking into account both quantitatively and qualitatively, proportionally to the planning period.

2. Discussion and Results

In the context of artificial intelligence technologies, the development of management decisions related to the accounting of product production costs and costing involves comparing two or more options in solving problems and choosing the optimal one. This requires the development of functional, software, information support and other measures for conducting empirical research on computers.

Functional maintenance is based on the models and algorithms of the production program, taking into account the features of cost calculation and accounting of production costs in grain processing enterprises. The relationship between them is based on a single database.

In information processing, the results entered into the information source and printed are divided into separate groups. The information entered into memory forms a set of information related to the accounting of product production costs and cost calculation [1; 459 - 471].

Based on the data in the computer memory, the system of accounting for product production costs and cost price calculation indicators is analyzed. Based on the results obtained from the calculation iterations in the study, a decision is made to continue or terminate the experiment. Based on the principle of systematic information and logical connections of the problem, we have developed a scheme for assessing the effectiveness of accounting for product production costs and cost price calculation at grain processing enterprises based on functional, software and information support (Figure 1).

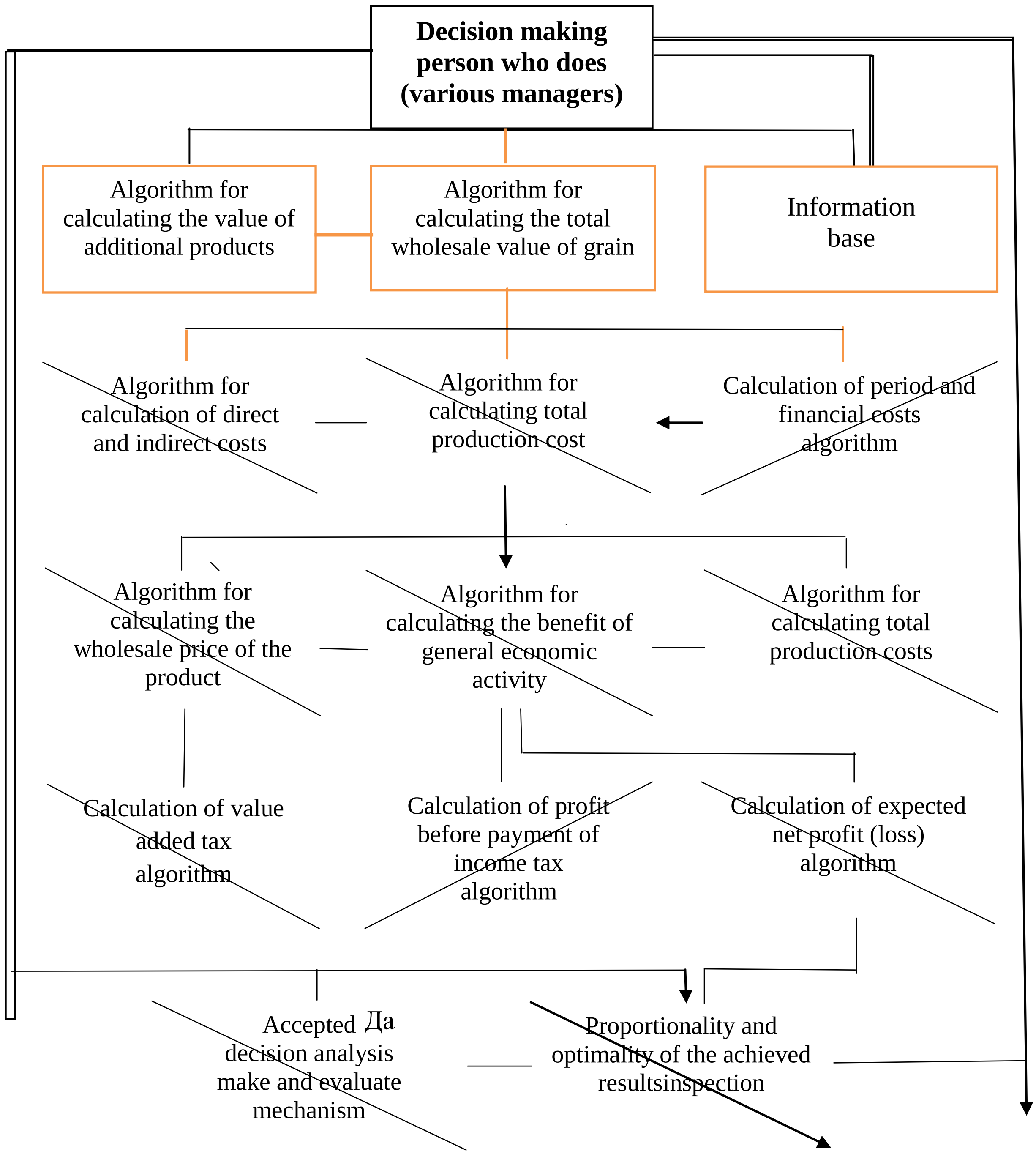

Fig. 1. A mechanism for keeping track of product production costs and evaluating cost calculations

To effectively manage the accounting of production costs and cost calculation of products, it is possible to calculate complex production costs for individual types of grain products and estimate cost calculation through scenarios developed in the framework of the project.In this case, if the results achieved when managers at different levels access the information database are not satisfactory, the procedure is repeated until a positive result is achieved, and decisions on alternative options are compared.

Tab. 1. Calculation of production costs and unit cost of flour products at "Dostlikgrainproducts" JSC according to the scenario*

(sum/ton)

Indicators	Actually	Scenarios		
		1	2	3
Production volume of flour products, tn	1	1	1	1
Amount of grain to be consumed, tn	43509,12	43509,12	43509,12	43509,12
Wholesale price of grain	55,70	55,70	55,70	55,70
Initial wholesale value of grain	1797826,00	2423253,02	2423253,02	2423253,02
Transportation costs - total	87493,98	88368,92	89243,86	90118,80
from this:				
a) railway costs	0,00	0,00	0,00	0,00
b) car expenses	44950,99	45400,50	45850,01	46299,52
c) domestic transportation costs	15575,99	15731,75	15887,51	16043,27
g) savings percentage	26967, 00	27236,67	27506,34	27776,01
The total cost of the grain, including transportation costs	1885320,09	2511621,95	2512496,89	2513371,83
Additional products - total	320169,01	323370,70	326572,39	329774,08
from this:				
a) bran	292100,99	295022,00	297943,01	300864,02
b) grain waste	28068,02	28348,70	28629,38	28910,06
The total value of grain after the separation of by-products	1565151,08	1580802,59	1596454,10	1612105,61
Grain value lost in transportation, storage and production	57507,00	58082,07	58657,14	59232,21
Direct and indirect costs	416071,00	420231,72	424392,43	428553,14
Fuel	2533,00	2558,33	2583,66	2608,99
Spare parts	13927,00	14066,27	14205,54	14344,81
Building materials	2004,00	2024,04	2044,08	2064,12
Other materials - total	65862,00	66484,26	67142,52	67800,78
from this:				
a) vitamin	28379,00	28662,79	28946,58	29230,37
b) thread	250,00	252,50	255,00	257,50
c) label	1105,00	1116,05	1127,10	1138,15
d) sack	31143,00	31454,43	31765,86	32077,29
e) others	4949,00	4998,49	5047,98	5097,47
Expenses paid to suppliers and contractors	52825,00	53353,25	53881,50	54409,75
from this:				
a) electricity costs	39461,00	39855,61	40250,22	40644,83
b) water costs	510,00	515,10	520,20	525,30
c) gas costs	0,00	0,00	0,00	0,00
d) others	12854,00	12982,54	13111,08	13239,62

Salary	187992,00	189871,92	191751,84	193631,76
Single social payment	22559,01	22784,60	23010,19	23235,78
Depreciation of fixed assets	68405,00	68405,00	68405,00	68405,00
Production cost - total	2038729,09	2059116,38	2079503,67	2099890,96
Period expenses - total	95681,86	96068,48	96455,10	96841,72
from this:				
a) administrative expenses	13648,00	13784,48	13920,96	14057,44
b) selling expenses	25014,00	25264,14	25514,28	25764,42
c) other operating expenses	57019,86	57019,86	57019,86	57019,86
from this:				
land tax	11337,00	11337,00	11337,00	11337,00
water tax	114,00	114,00	114,00	114,00
property tax	8301,00	8301,00	8301,00	8301,00
other expenses	37267,86	37267,86	37267,86	37267,86
Costs of financial activity	5064,00	5064,00	5064,00	5064,00
from this:				
loan interest	5064,00	5064,00	5064,00	5064,00
Total production costs - everything	2139474,95	2160248,86	2181022,77	2201796,68
The benefit of the general economic activity	21395,05	22229,84	23064,63	23899,42
Profit before income tax	3209,26	3334,48	3459,69	3584,91
The wholesale value of the product	2160870,00	2182478,70	2204087,40	2225696,10
Value added tax	570608,75	576314,84	582020,93	587727,01
Wholesale price of flour products (including value added tax)	2731478,75	2758793,54	2786108,33	2813423,11
Net profit	18185,79	18895,36	19604,93	20314,50
Cost-effectiveness	0,89	0,92	0,94	0,97
Cost-effectiveness	0,85	0,87	0,90	0,92

According to the information in table 1, according to the scenarios, 2139474,95 soums, 2160248,86 soums, 2181022,77 soums and 2201796,68 soums may be spent on production costs at the enterprise for the preparation of 1 ton flour product unit. The cost of the product unit is 2038729,09 soums, 2059116,38 soums, 2079503,67 and 2099890,96 soums, respectively. As a result, the company's net profit from 1 ton of flour product is 18185,79 soums, 18895,36 soums, 19604,93 soums and 20314,50 thousand soums, respectively; the rate of return on cost is 0,89%, 0,92%, 0,94% and 0,97%; the rate of return on production costs increases by 0,85%, 0,87%, 0,90% and 0,92%.

Table 2. Calculation of production costs and unit cost of products according to the scenarios of fodder products at "Dostlikgrainproducts" JSC

(in soums/kg)

Indicators	Actually	Scenario		
		1	2	3
Production volume of dry fodder products, tn	1	1	1	1
Consumption of raw materials - total, tn	101,00	101,00	101,00	101,00
a) bran, tn	54,44	54,44	54,44	54,44
b) thus, tn	2,23	2,23	2,23	2,23
c) corn grain, tons	0,00	0,00	0,00	0,00
d) flour, tons	2,93	2,93	2,93	2,93
d) lime flour, tons	2,00	2,00	2,00	2,00
e) wheat waste (70-85%), tn	1,41	1,41	1,41	1,41
or) wheat waste (50-75%), tn	28,28	28,28	28,28	28,28
g) barley, tn	4,90	4,90	4,90	4,90
Price of raw materials:				
a) bran	925,45	934,70	943,96	953,21
b) way	2200,00	2222,00	2244,00	2266,00
c) corn kernels	3043,48	3073,91	3104,35	3134,78
d) flour	1130,00	1141,30	1152,60	1163,90
d) lime flour	390,00	393,90	397,80	401,70
e) wheat waste (70 – 85%)	876,16	884,92	893,60	902,44
or) wheat waste (50 – 75%)	626,16	632,42	638,68	644,94
g) barley	2825,00	2853,25	2881,50	2909,75
Cost of raw materials:				
a) bran	503804,64	508842,68	513931,11	519070,42
b) way	26664,00	26930,64	27199,95	27471,95
c) corn kernels	175213,03	176965,16	178734,81	180522,16
d) flour	33097,70	33428,68	33762,96	34100,59
d) lime flour	7878,00	7956,78	8036,35	8116,71
e) wheat waste (70 – 85%)	12388,86	12512,75	12637,88	12764,25
or) wheat waste (50 – 75%)	177078,05	178848,83	180637,32	182443,69
g) barley	139809,25	141207,34	142619,42	144045,61
Mechanical losses – 1%	0,00	0,00	0,00	0,00
Total cost of raw materials	1075934,52	1086692,86	1097559,79	1108535,38
Electricity	6696,00	6762,96	6829,92	6896,88
Transportation costs - total	4967,46	5017,13	5066,81	5116,48
from this:				
a) railway costs	0,00	0,00	0,00	0,00
b) car expenses	3356,25	3389,82	3423,38	3456,94
c) domestic transportation costs	1611,21	1627,32	1643,43	1659,54
Spare parts	6800,10	6868,10	6936,10	7004,10
Salary	76146,00	76907,46	77668,92	78430,38

Single social payment	9137,2	9228,90	9320,27	9411,65
Storage of equipment	14152,53	14152,53	14152,53	14152,53
Depreciation of fixed assets	19686,96	19686,96	19686,96	19686,96
Other expenses	15955,79	15955,79	15955,79	15955,79
Production cost - total	1229475,88	1241272,68	1253177,08	1265190,15
Period expenses - total	104035,58	104035,58	104035,58	104035,58
from this:				
a) administrative expenses	15743,68	15743,68	15743,68	15743,68
b) selling expenses	3938,58	3938,58	3938,58	3938,58
c) other operating expenses	84353,32	84353,32	84353,32	84353,32
from this:				
land tax	3232,35	3232,35	3232,35	3232,35
water tax	0,00	0,00	0,00	0,00
property tax	4092,00	4092,00	4092,00	4092,00
other expenses	77028,96	77028,96	77028,96	77028,96
Costs of financial activity	3577,58	3577,58	3577,58	3577,58
Total production costs - everything	1337089,03	1348885,84	1360790,24	1372803,31
The benefit of the general economic activity	63055,97	65260,61	67497,68	69767,49
Profit before income tax	9458,00	10404,23	11350,07	12295,91
The wholesale value of the product	1400145,00	1414146,45	1428287,91	1442570,79
Value added tax	210021,75	212121,97	214243,19	216385,62
The wholesale value of the product(including value added tax)	1610166,75	1626268,42	1642531,10	1658956,41
Net profit	53597,57	54856,38	56147,60	57471,57
Cost-effectiveness	4,36	4,42	4,48	4,54
Cost-effectiveness	4,01	4,07	4,13	4,19

According to the information in table 2, according to the scenarios, 1337089.03 soums, 1348885.84 soums, 1360790.24 soums and 1372803.31 soums may be spent on production costs for the production of 1 kg of fodder product at the enterprise. The unit cost of 1 kg of fodder product is 1229475.88 soums, 1241272.68 soums, 1253177.08 and 1265190.15 soums, respectively. As a result, the net profit from 1 kg of fodder product in the enterprise is 53597.57 soums, 54856.38 soums, 56147.60 soums and 57471.57 thousand soums, respectively; the rate of return on cost is 4.36%, 4.42%, 4.48% and 4.54%; the rate of return on production costs increases by 4.01%, 4.07%, 4.13% and 4.19%.

So, "Dostlikgrainproducts" JSC products According to empirical studies conducted at the joint-stock company, the increase in the net profit of flour products from 0.89% to 0.97% and the net profit of compound feed products from 4.36% to 4.54% at the enterprise has a positive effect on the trend of increasing the volume of flour and compound feed products, and creates a positive trend in increasing the economic efficiency of the activity, and the impact of the cost factor on the trend of product production leads to an increase in the volume of products.

Now, with the help of artificial intelligence technologies and scientifically based optimal decision-making method, mid- and long-term forecast indicators until 2030 are presented for the financial strategy of distribution of production costs and cost calculation management of flour and coarse feed products of "Dostlikgrainproducts" JSC.

Tab. 3. Retrospective and forecast indicators on the distribution of complex production costs of flour and feed products of "Dostlikgrainproducts" JSC***

Year	Flour products, one thousand soums				Fodder product, thousand soums			
	Flour volume of production	Productioncost	General expenses	Net profit	Eat carefully. volume of production	Production cost	General expenses	Net profit
2011	57909487	42723138	44834389	364019	18291291	16061750	17467537	700191
2012	56997084	42050006	44127993	358283	18003099	15808685	17192323	689159
2013	59495393	45183169	47415988	373988	18792215	16501615	17945901	719366
2014	60304560	44452444	46649153	379094	19047798	16726045	18189974	729150
2015	59824732	44080072	46258379	376058	18896240	16592960	18045241	723349
2016	61956058	46622713	48926670	389455	19569440	17184104	18688124	749119
2017	65451199	48184926	50566083	411426	206 73416	18153515	19742382	791379
2018	64072091	45238846	47474416	402757	20237811	17771006	19326394	774704
2019	67243643	49138897	51567196	422693	21239577	18650666	20283046	813052
2020	65394783	46133647	48413436	411071	20655596	18137867	19725364	790697
2021	69085175	50775069	53284223	434269	20154762	17698081	19247086	771525
2022	70012188	49337244	51775294	440096	23802465	20901090	22730513	911159
2023	70921646	49978086	52447855	445813	24170342	21068800	22912824	918489
2024	72335430	51065465	53588955	454700	24170314	20521536	22317661	925241
2025	73922326	51779166	54337922	464675	24351702	21067151	22911030	932184
2026	75172372	52207362	54787276	472533	24900304	21532222	23416807	951575
2027	76704585	53080441	55703497	482164	25615827	22094087	24027848	978685

2028	78253222	53774717	56432079	491899	26364837	22677177	24661973	1007054
2029	79463716	54236622	56916807	499508	27025721	23177485	25206070	1032041
2030	80783934	55019059	57737906	507807	27745853	23722775	25799086	1059285

***Compiled based on financial and statistical data of "Doslik Grain Products" JSC.

According to the information in table 3, the total costs for the production of flour products from 2024 to 2030 are from 53588955 thousand soums to 57737906 thousand soums, the cost of production is from 51065465 thousand soums to 55019059 thousand soums, and the net profit is from 454700 thousand soums to 507807 thousand soums. can increase. The total costs for the production of feed products can increase from 22317661 thousand soums to 25799086 thousand soums, the cost of production from 20521536 thousand soums to 23722775 thousand soums, and the net profit can increase from 925241 thousand soums to 1059285 thousand soums.

Figure 3 shows a graph based on forecast data on flour production for the period from 2024 to 2030. The graph shows that the flour production function has the form y = 19793x2 + 84023x + 6e7, the correlation between the function and the factors is R^2 = 0.9763; the function on the cost of production has the form y = 683884x + 4e7, and the correlation between the function and the factors is R^2 = 0.9283; the function on total production costs has the form y = 651682x + 4e7, and the correlation between the function and the factors is R^2 = 0.9283 [1; 459 - 471].

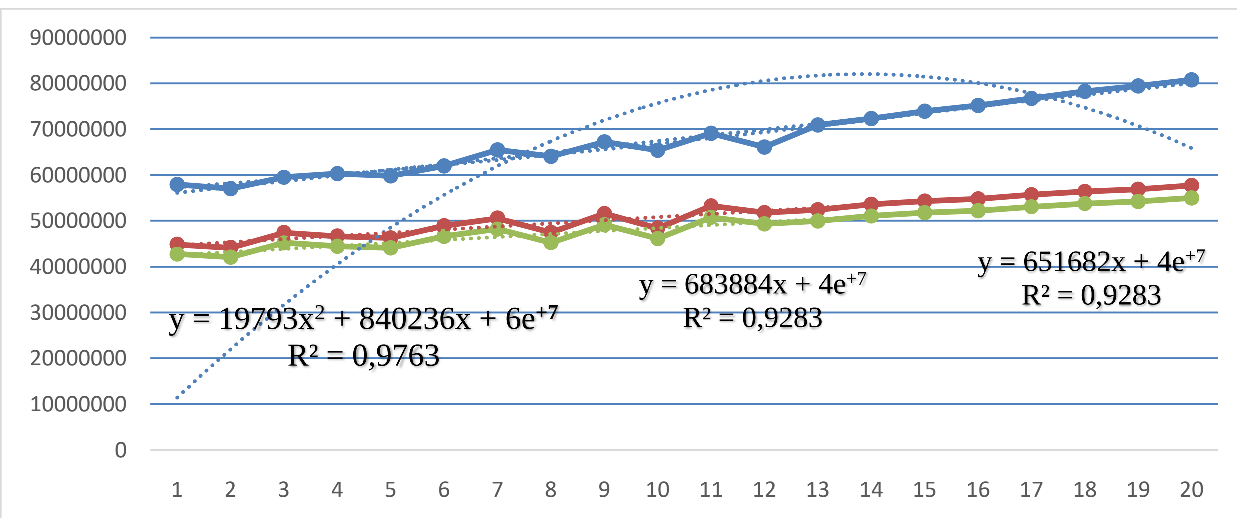

Fig. 2. Forecast of indicators of flour products

Figure 3 shows a graph based on forecast data on the production of mixed feed flour products for the period from 2024 to 2030. In the graph, the flour production function has the form y = 13367x2 + 239893x + 2e7, the correlation between the function and the factors is R^2 = 0.9588; the function on the cost of production has the form y = 459461x + 2e7, and the correlation between the function and the factors is R^2 = 0.9419; the function on total production costs has the form y = 422483x + 1e7, and the correlation between the function and the factors is R^2 = 0.9419.

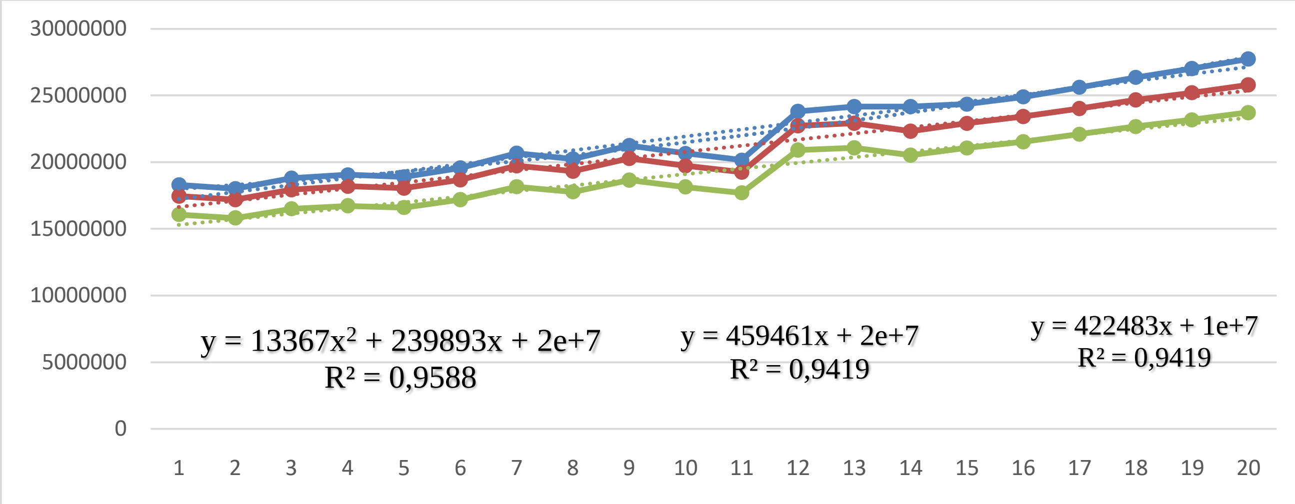

Fig. 3. Forecast of performance of dry feed products

Figure 4 shows a graph based on the forecast data for net profit on flour and compound feed products for the period from 2024 to 2030. In the graph, the net profit function for flour products has the form y = 503.78x2 + 9195.3x + 679528, the correlation between the function and the factors is $R^2 = 0.9596$; the net profit function for compound feed products has the form y = 351053e0.0186x, and the correlation between the function and the factors is $R^2 = 0.9851$.

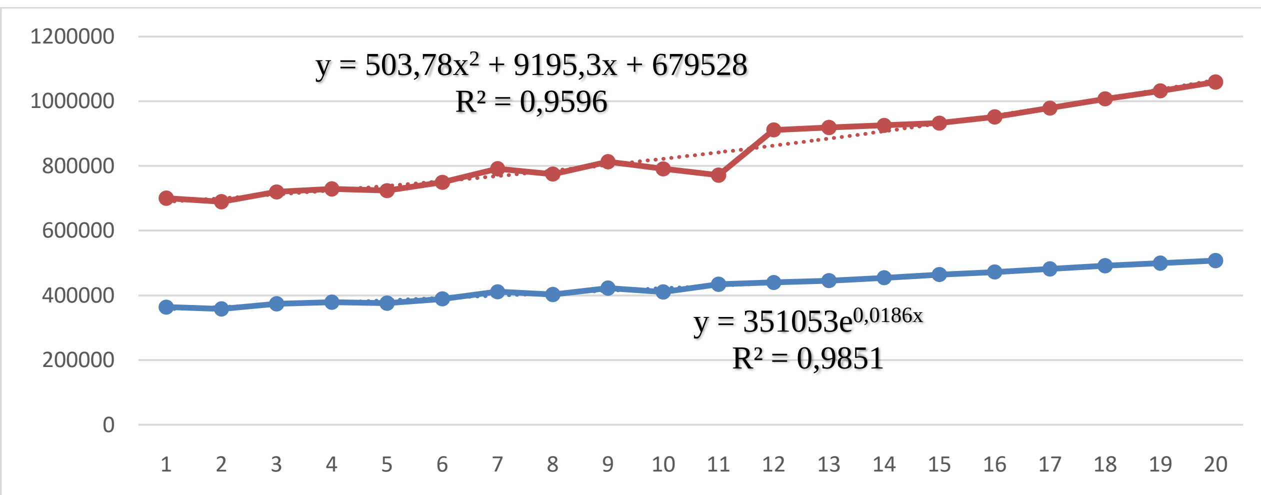

Fig.4. Forecast of net profit figures from flour and feed products

So, "Dostlikgrainproducts"**products**the joint-stock company has the opportunity to explore internal production resources, rationally use internal potential, increase the production volume of high-quality flour and compound feed products, and reduce overall costs in order to increase production efficiency and reduce costs.

CONCLUSION

An empirical study conducted algorithms for the accounting of production costs and cost calculation of flour and compound feed products at grain processing enterprises were developed, the efficiency of a particular type of product was assessed, and a forecast for making scientifically based optimal decisions based on scenario forecast indicators was provided on the financial strategy for accounting of production costs per unit of flour and compound feed products and cost calculation management based on artificial intelligence technologies. According to the results of the study, compound feed products bring a larger amount of cash income to the enterprise compared to flour products and increase the amount of net profit.

Keeping track of production costs per unit of flour and fine feed products based on artificial intelligence technologies and making scientific-based optimal decisions on the basis of scenario forecast indicators for the financial strategy of cost calculation management, searching for internal reserves of production to reduce costs, increasing the production volume of quality flour and fine feed products provides an opportunity to increase the economic efficiency of the enterprise.

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AI WEED DETECTION AND MONITORING SYSTEM USING COMPUTER VISION

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DOI: 10.5958/2249-7137.2025.00028.9

ABSTRACT

The innovation behind the Weed Eliminator AI Using Arduino lies in the realm of Artificial Intelligence (AI) and Internet of Things (IoT). These technologies empower the system to identify and address one of agriculture's most persistent challenges: weeds. By leveraging AI for real-time weed detection and Arduino for precise control, this project transforms traditional weed management into a highly efficient, automated process. One key AI technique utilized in this project is object detection, specifically through the YOLO (You Only Look Once) model. Imagine the system's camera acting as a vigilant observer, scanning the field and identifying weeds with remarkable accuracy. The YOLO model processes these images in real time, pinpointing the exact locations of weeds while ignoring crops. This ensures targeted spraying, minimizing herbicide wastage and preventing crop damage. The system's capabilities extend beyond simple detection. By integrating Arduino, the project achieves seamless communication between the AI model and the spraying mechanism.

The Arduino acts as a central controller, receiving commands from the YOLO model to activate a 12V DC motor that controls the sprayer. This level of automation eliminates the need for *manual intervention, making the process faster, more precise, and less labour-intensive. Furthermore, the project incorporates energy-efficient design principles. The entire setup is powered by a 12V battery, ensuring portability and adaptability to different field conditions.*

KEYWORDS: *Real-Time Object Detection, Audio Feedback, Obstacle Avoidance, Navigation Assistance And User-Friendly Interface.*

1. INTRODUCTION

The agricultural industry is continually evolving, with advancements in technology playing a crucial role in reshaping traditional farming practices. One of the most significant challenges faced by farmers today is effective weed management. Weeds not only compete with crops for nutrients, water, and sunlight but can also harbor pests and diseases, affecting overall crop yield and quality. Traditional weed management methods often rely on indiscriminate herbicide spraying, which leads to excessive chemical use, environmental degradation, and increased costs for farmers. As the need for more sustainable farming practices grows, innovative solutions that combine technology with precision are becoming essential in addressing these challenges. To overcome these issues, this project introduces the Weed Eliminator AI Using Arduino, a smart, automated system designed to detect and eliminate weeds efficiently while minimizing herbicide usage. The system leverages cutting-edge Artificial Intelligence (AI) and computer vision to distinguish between weeds and crops, enabling precise application of herbicides only where needed. By incorporating the YOLO (You Only Look Once) model, an advanced object detection technology, the system provides real-time, accurate identification of weeds, ensuring that crops remain unaffected by the spraying process. This not only reduces the environmental impact but also increases farming efficiency by targeting only the problematic areas. The use of AI and automation in agriculture has the potential to revolutionize traditional farming methods, and this project demonstrates how these technologies can be applied to weed management. It discusses how AI and computer vision technologies can automate the identification and removal of weeds, thus reducing herbicide use.

2.EXISTING SYSTEM

The current weed management systems in agriculture primarily rely on conventional methods such as manual weeding and broad-spectrum herbicide spraying. While effective to some extent, these systems have significant drawbacks, including high labour costs, environmental pollution, and inefficient use of chemicals. Traditional herbicide spraying often leads to the overuse of chemicals, harming beneficial plants and polluting soil and water. Moreover, manual weeding is labour-intensive and time-consuming, making it an impractical solution for large-scale farms. These traditional methods do not leverage modern technologies to improve efficiency or sustainability, resulting in increased costs and environmental impact.

2.1 DRAWBACKS IN EXISTING SYSTEM

- High Costs of Drones and Automation: Drones and automated weed detection systems can be expensive to implement and maintain, making them less accessible for small to medium-scale farmers.
- Inefficient Herbicide Usage: Traditional herbicide spraying systems apply chemicals indiscriminately, leading to high costs and environmental harm due to overuse.

- Complex System Integration: Many current systems do not integrate weed detection with spraying mechanisms, causing inefficiencies and increasing operational costs.
- Environmental Harm of Over-Spraying: Over-spraying with herbicides in traditional systems harms non-target plants and contributes to soil and water pollution, impacting sustainability. Traditional herbicide spraying often leads to the overuse of chemicals, harming beneficial plants and polluting soil and water.

2.2 PROPOSED SYSTEM

The Weed Eliminator AI Using Arduino is designed to revolutionize weed management by addressing the limitations of traditional farming practices. Unlike conventional methods that rely on broad-spectrum herbicide spraying and manual labor, this system uses artificial intelligence (AI) and real-time image processing to precisely identify and target weeds. The system's core functionality revolves around the YOLO object detection model, which identifies weeds from images captured by a camera mounted on a sprayer. This ensures that herbicide is only applied where it is needed, reducing waste and promoting environmentally sustainable farming practices. At the heart of the proposed system lies the integration of Arduino-based control to operate the herbicide sprayer.

Once weeds are detected, the AI system sends a signal to the Arduino, which activates a 12V DC motor to spray the targeted area. This seamless interaction between AI, real-time image processing, and automated control ensures that the spraying process is both efficient and precise. By automating weed detection and herbicide application, the system not only reduces labor costs but also enhances operational efficiency, making it suitable for farms of various sizes. The AI-powered detection system ensures that only weeds are targeted for herbicide application, minimizing the risk of harming crops or other beneficial plants. Unlike traditional systems that indiscriminately spray herbicides, the proposed system uses machine learning algorithms to differentiate between weeds and crops with high accuracy. This precision minimizes the environmental impact, helping farmers reduce chemical usage, safeguard soil health, and preserve biodiversity within their fields.

In addition to providing real-time, contextual accuracy, the Weed Eliminator AI system can be easily scaled to fit different types of agricultural environments. The seamless user experience is another key feature of the proposed system. which identifies weeds from images captured by a camera mounted on a sprayer. This ensures that herbicide is only applied where it is needed, reducing waste and promoting environmentally sustainable farming practices. At the heart of the proposed system lies the integration of Arduino-based control to operate the herbicide sprayer. Once weeds are detected, the AI system sends a signal to the Arduino, which activates a 12V DC motor to spray the targeted area. Eliminator AI system can be easily scaled to fit different types of agricultural environments. The seamless user experience.

2.3 PROBLEM DEFINITION

The current methods for weed management in agriculture are often inefficient, environmentally harmful, and labor-intensive. Traditional practices like broad-spectrum herbicide spraying and manual weeding not only lead to significant chemical waste but also pose risks to the surrounding ecosystem, including soil degradation and water contamination. These methods fail to target weeds with the precision necessary to avoid damaging crops or non target plants. As a result, farmers are forced to use more chemicals than required, leading to increased costs and environmental harm.

The inefficiency of these systems has become a growing concern as agricultural operations look for more sustainable and cost-effective solutions. Additionally, manual weed control methods are highly labor-intensive, requiring significant human effort, especially in large agricultural fields. This not only increases the cost of production but also strains the available workforce, making it difficult to manage extensive farming operations. As the agricultural industry continues to face labor shortages, these manual methods become even more impractical. The need for automated solutions that reduce human labor while improving efficiency has never been more urgent. Traditional systems simply cannot meet the demands of modern, large-scale agriculture. Another major issue is the lack of precision in current weed detection systems. While there have been advancements in using cameras and sensors for weed identification, many existing technologies struggle to accurately differentiate between weeds and crops, particularly in complex environments. This results in the misapplication of herbicides, which can damage crops or leave weeds untreated.

Current systems often rely on simple image processing methods that lack the sophistication needed for real-time, accurate identification and decision-making, leading to inefficiencies and poor weed management outcomes. The need for automated solutions that reduce human labor while improving efficiency has never been more urgent. Traditional systems simply cannot meet the demands of modern, large-scale agriculture. Another major issue is the lack of precision in current weed detection systems. While there have been advancements in using cameras and sensors for weed identification, many existing technologies struggle to accurately differentiate between weeds and crops, particularly in complex environments.

2.4 OBJECTIVE OF PROPOSED SYSTEM

The primary objective of the Weed Eliminator AI Using Arduino system is to develop an innovative, automated solution for weed management that enhances precision, reduces environmental impact, and lowers operational costs. Unlike traditional methods, this system leverages artificial intelligence (AI) to accurately detect weeds and target herbicide application only where needed. By integrating advanced image processing and machine learning algorithms, the system aims to distinguish between crops and weeds in real time, ensuring that herbicide is sprayed precisely and efficiently, reducing waste and minimizing the impact on non-target plants.The proposed system seeks to automate the weed management process, reducing the need for labor-intensive methods such as manual weeding.

The integration of Arduino-based control enables seamless automation, activating a 12V DC motor and spraying herbicide only when weeds are detected. By eliminating the need for manual intervention, the system allows farmers to focus on other critical tasks, ultimately improving overall farm productivity and efficiency while reducing labor costs. The overarching goal of the Weed Eliminator AI Using Arduino system is to provide cost-effective, eco-friendly, and automated weed management that improves the efficiency and sustainability of agricultural practices. The objective is to create a system that will help farmers manage their crops effectively, ensuring better yields and healthier ecosystems for the future.

2.5 FEATURES OF PROPOSED SYSTEM

- Precision Weed Detection
- Automated Herbicide Application
- Environmentally Friendly
- Real-Time Operation
- Easy Integration with Existing Systems
- Adaptable and Scalable

3. SYSTEM SPECIFICATION

3.1HARDWARE REQUIREMENTS

Hardware refers to the physical components of a computing system, and it plays a critical role in enabling the software to perform its tasks efficiently. The following outlines the minimum hardware requirements for the Weed Eliminator AI Using Arduino system, ensuring smooth operation for weed detection and herbicide spraying.

- PROCESSOR – i3 Intel
- RAM – 4GB
- HARD DISK – 128 GB
- Arduino IDE
- ESP32 CAMERA LIBRARY

3.2 SOFTWARE REQUIREMENTS

Software requirements define the necessary software tools, libraries, and operating systems needed to run and optimize the Weed Eliminator AI Using Arduino system. These prerequisites ensure that the application functions smoothly and efficiently, especially when integrating AI-based weed detection and real-time herbicide application. The following outlines the key software requirements for this project.

3.2.1 OPERATING SYSTEM- WINDOWS 10

An operating system (OS) is the program that, after being initially loaded into the computer by a boot program, manages all of the other application programs in a computer. The application programs make use of the operating system by making requests for services through a defined application program interface (API). Software Requirements deal with defining software resource requirements and prerequisites that need to be installed on a computer to provide optimal functioning of an application.

3.3 INTEGRATED DEVELOPMENTENVIRONENT

VS Code is particularly well-suited for Python development due to its support for Python-specific extensions and debugging tools, making it easy to write, run, and debug Python code. Its powerful IntelliSense feature provides code completion and suggestions, reducing development time and increasing project productivity. Additionally, the IDE supports version control integration with Git, providing a seamless experience for managing collaborating.

3.4 PACKAGES AND LIBRARIES

A package is a collection of related modules that work together to provide specific functionality, often stored within a folder and imported as a module in code. A library, on the other hand, is an overarching term referring to a bundle of code that may include multiple modules for various functions. Libraries enable developers to leverage pre-existing solutions for common tasks, streamlining development. For instance, the Standard Library in Python comes bundled with common functionalities, such as handling JSON data, sending emails, or parsing XML files, allowing developers to work without having to download external modules. A library, on the other hand, is an overarching term referring to a bundle of code that may include multiple modules for various functions.

4.SYSTEM DESIGN

4.1 INTRODUCTION

A data flow diagram (DFD) is a graphical or visual representation using a standardized set of symbols and notations to describe a business's operations through data movement. They are often elements of a formal methodology such as Structured Systems Analysis and Design Method (SSADM). A data- flow diagram is a way of representing a flow of data through a process or a system (usually an information system). The DFD also provides information about the outputs and inputs of each entity and the process itself. A data-flow diagram has no control flow there are no decision rules and no loops. Specific operations based on the data can be represented by a flowchart. DFD does not have control flow and no loops or decision rules a represent. Specific operations depending on the type of data can be explained by a flowchart.

4.1.1 CONTEXT DIAGRAM

A special data flow diagram (DFD) known as context diagram that represents an entire system as a single process and highlights the interfaces between the system and the outside entities.

4.2 PRIMITIVE SYMBOLS

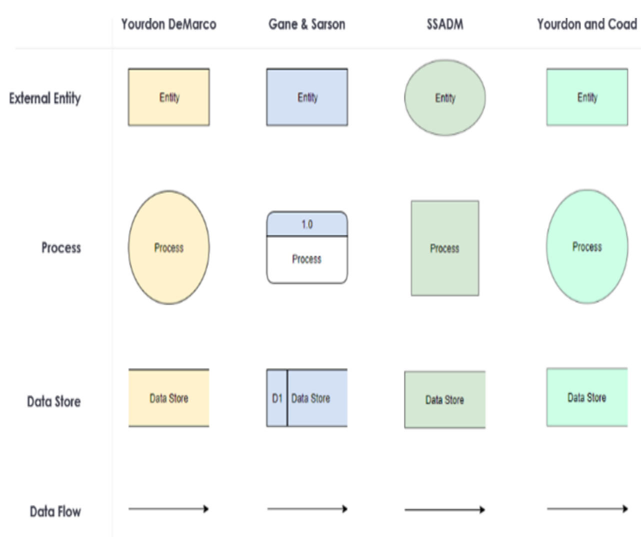


Fig1: Primitive Symbols

Symbols of DFD are:

- External Entity
- Process
- Data Store
- Data flow

4.2.1 PROCESS

A process in a data flow diagram represents a function or transformation that takes one or more inputs and produces one or more outputs associated with a specific function or task, and its purpose is to modify, manipulate, or transform data as it flows through the system. Processes can be as simple as data validation or as complex as advanced calculations or decision- making algorithms.

4.2.2 DATAFLOW

Data flows in a DFD represent the movement of data from one component (external entity, process, or data store) to another. They are depicted as arrows connecting these components, with labels indicating the data being transferred. Data flows represent the paths that data takes as it enters, exits, or transform data as it flows through the system. Processes can be as simple as data validation or as complex as advanced calculations or decision- making algorithms. circulates within the system. By showing data flows, DFDs help clarify the relationships between components and the data they interact with, allowing stakeholders to understand data movement and communication within the system.

4.2.3 DATASTORE

A data store, represented as a rectangle with a label in a DFD, represents a repository or storage location where data is persistently stored within the system. Data stores are used to depict databases, file systems, or any other means of storing data for future retrieval or reference. For example, in an inventory management system, a data store could represent a database containing product information. Any other means of storing data for future retrieval or reference.

4.2.4 EXTERNAL ENTITY

An external entity, also known as a "terminator" in DFD notation, represents external sources or destinations of data in a system. These entities are typically entities outside the system being analysed but interact with it. For example, in a retail system, customers, suppliers, and regulatory agencies could be external entities. DFDs use external entities to show how data flows into and out of the system, helping to define its boundaries and interfaces with external stakeholders.

4.3 DATAFLOW DIAGRAM

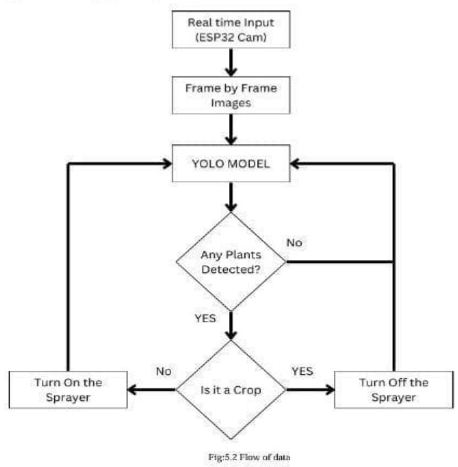
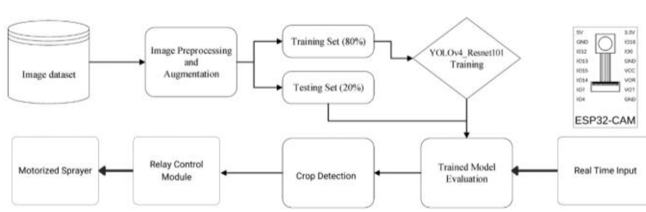


fig2. Data flow Diagram of the process

The Weed Eliminator AI Using Arduino system operates by processing real-time data from various components to detect and eliminate weeds in agricultural fields efficiently. The process begins when the system captures images of the field using an ESP32-CAM or similar camera. These images are sent to a laptop or local processing unit, where they are preprocessed for weed detection. The pre-processed images are then analyzed using a trained weed detection model (such as YOLO), which identifies the presence and location of weeds.If weeds are detected, the system sends a command to the Arduino microcontroller to activate a 12V DC motor, which controls the sprayer nozzle, releasing herbicide only where weeds are present. The system operates based on real-time feedback from environmental sensors, such as temperature, humidity, and soil moisture, to adjust the spraying mechanism for optimal performance.

The system logs data throughout the process, including sensor readings and spraying actions, for future analysis and optimization. Finally, the user receives feedback regarding the areas treated and the efficiency of the spraying process. This integrated data flow ensures that the system provides precise, targeted weed control, reducing herbicide usage and enhancing sustainability in agriculture. which identifies the presence and location of weeds. If weeds are detected, the system sends a command to the Arduino microcontroller to activate a 12V DC motor, which controls the sprayer nozzle, releasing herbicide only where weeds are present.

4.4 SYSTEM ARCHITECTURE



The Weed Eliminator AI Using Arduino system relies on a trained YOLO (You Only Look Once) model for accurate real-time weed detection. The training process for the YOLO model begins with collecting a diverse dataset of images containing both weeds and crops. This dataset is annotated, marking the positions of weeds within each image. The images are then processed and fed into the YOLO model, which learns to identify the unique features of weeds in comparison to surrounding crops. During training, the model adjusts its internal parameters to minimize prediction errors. After sufficient training on a large and diverse dataset, the YOLO model becomes proficient in recognizing weeds in new, unseen images.

Once trained, the YOLO model is deployed for real-time prediction. In the field, the system uses an ESP32-CAM or similar camera to capture images of the crops. These images are then processed locally or sent to a laptop where the YOLO model performs inference to detect and locate any weeds. The model identifies weeds by their unique characteristics, and if detected, it triggers the Arduino microcontroller to activate a 12V DC motor, which controls the sprayer nozzle to dispense herbicide. The process is powered by a 12V battery for portability and mobility across large agricultural areas. This setup ensures that herbicide is applied only where it is needed, reducing waste and environmental impact. The hardware components, such as the ESP32-CAM, Arduino, and DC motor, work seamlessly to execute the real-time prediction and spraying task efficiently.

4.5 DATA COLLECTION

For the Weed Eliminator AI project, the initial dataset is gathered through images taken in fields

with a variety of crops and weeds. This data collection process involves sourcing images from real-world agricultural settings, ensuring the dataset covers various environmental conditions and weed types. The images collected may come from multiple sources such as manual image capturing through the ESP32-CAM in the field or public agricultural datasets. However, the raw data collected is likely to present challenges, such as variations in lighting, angles, and weed/crop differences. These variations are crucial for training the model to work in diverse real-world environments. The collection phase ensures that the dataset is diverse enough to train the YOLO model on a wide range of weed detection scenarios.

4.6 DATA PRE-PROCESSING

The Data Preprocessing module plays a vital role in refining the raw data collected from the field before it is used for training the YOLO model. Preprocessing tasks focus on improving data quality to ensure effective training and inference. The first step in the process is image normalization, which standardizes lighting, brightness, and contrast across all images to reduce variations in appearance. Additionally, image augmentation techniques such as rotation, flipping, and scaling are applied to increase the diversity of training data and make the model more robust to different conditions.

Furthermore, the images are labeled with precise annotations to distinguish between crops and weeds, which is essential for supervised learning. The cleaned and pre-processed data is then ready for training the model, ensuring that the YOLO model can accurately identify weeds across different field conditions.

4.7 FEATURE IDENTIFICATION

The Feature Identification module is critical for selecting the key attributes necessary for the weed detection model. In the case of the Weed Eliminator AI, these features are primarily related to the visual aspects of the images, such as the size, shape, and color of the weeds and crops. Using domain knowledge in agriculture, features like leaf shape, plant height, and color contrast between weeds and crops are identified as essential to distinguishing between the two. Image processing techniques, such as edge detection and color histograms, help extract these features from the images, enabling the YOLO model to focus on the most relevant characteristics. Additionally, feature extraction aids in improving the accuracy of the weed detection model by allowing it to focus on the differences between crops and weeds that are most indicative of their presence in an image.

4.8 ENCODING AND TRANSFORMATION

The Encoding and Transformation module is responsible for preparing the image data in a format that is suitable for the YOLO model to process. While YOLO primarily works with images, certain transformations need to be performed to ensure the data is ready for the model. For instance, the images are resized to a consistent resolution to standardize the input size. Additionally, the YOLO annotations, which specify the location of weeds within the image, are converted into a format compatible with the model. These annotations usually include bounding box coordinates, which outline the weed's location within the image. The transformation also includes encoding the image labels and bounding boxes into a structured format that the model can understand, ensuring that it learns the correct association between the input image and the presence of weeds. This transformation process ensures the YOLO model can effectively detect weeds during inference.

4.9 DATA SPLITTING

The Data Splitting module divides the dataset into two main subsets: one for training the YOLO model and another for testing its performance. The training set is used to teach the model how to detect weeds based on the labeled images of crops and weeds. It contains a diverse range of images and annotations that expose the model to various weed types, field conditions, and image orientations. The testing set, on the other hand, is used to evaluate the performance of the trained model. It consists of images that were not part of the training data, allowing for an unbiased assessment of the model's ability to generalize to new, unseen environments. This separation ensures that the model is not overfitting to the training data and can accurately detect weeds in a variety of conditions during real-time operation.

4.9 MODEL SELECTION AND TRAINING

The Model Selection and Training module is the heart of the Weed Eliminator AI system. The primary goal is to choose the best model for detecting weeds from the dataset. Given the visual nature of the task, the YOLO model, a well-known real-time object detection model, is chosen for its efficiency and accuracy. YOLO's architecture is designed to handle image data and detect objects in real time, making it ideal for weed detection in fields. During the training phase, the model is fed the pre-processed and annotated images, learning to recognize patterns associated with weeds, such as shape, color, and texture. The training process involves fine-tuning the model’s parameters, such as weights and biases, using backpropagation and optimization techniques to minimize prediction errors. After sufficient training, the model becomes capable of accurately detecting weeds in real-time, activating the Arduino system to trigger the sprayer when weeds are detected. The model is continuously refined using evaluation metrics like accuracy, precision, and recall to ensure that it provides reliable weed detection in diverse field conditions.

5. SYSTEM TESTING

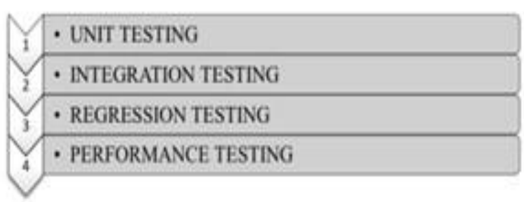
5.1 INTRODUCTION

Testing serves a fundamental purpose in the development and quality assurance of software and systems. Its overarching goal is to identify and rectify errors, faults, or weaknesses present in a work product. By systematically examining a software application or system, testing seeks to uncover any conceivable issues that might impede its functionality or reliability. This process extends to evaluating the components, sub-assemblies, assemblies, and the final product to ensure it meets predefined standards and specifications. Ultimately, testing is the means through which software systems are exercised to verify that they align with their intended purpose, fulfill user expectations, and operate without unacceptable failures.

The testing landscape encompasses various types, each tailored to address specific testing requirements and objectives. These test types include unit testing, integration testing, system testing, acceptance testing, regression testing, and more. Each type has a defined scope and focus, ranging from scrutinizing the behavior of individual software units to assessing the overall system's functionality, performance, and user experience. Through this diversity of test types, the testing process aims to comprehensively validate the software's correctness, robustness, and suitability for its intended use.

- Testing the basic logic of the model
- Managing the model performance by using manual testing
- Evaluating the accuracy of the model
- Make sure that the achieved loss is acceptable for the task
- Checking model performance on real data

5.2 TYPES OF TESTING



5.3 UNIT TESTING

Unit testing is indispensable in ensuring the individual components of the Weed Eliminator AI system function as intended. Each software and hardware module is treated as a standalone unit, and comprehensive test cases are crafted to verify their behavior in isolation. For instance, the YOLO model's ability to identify weed patterns is tested using a diverse dataset, ensuring consistent detection across varying lighting conditions, weed species, and background complexities.Arduino's control logic is another focus area in unit testing. Tests verify that specific signals from the YOLO model, such as weed detection coordinates, result in precise motor activation and sprayer operations. Scenarios include both valid detections and edge cases, such as false positives or prolonged inactivity.The motor and sprayer unit undergo hardware-specific testing to confirm their responsiveness to Arduino's commands. For instance, tests check if the motor starts and stops accurately, avoiding over-spraying or missing weeds. These validations extend to physical conditions like varying field terrain and temperature, ensuring robust performance.

Battery management is also a critical focus of unit testing. Battery drainage rates, voltage consistency, and power delivery are evaluated to ensure the system performs reliably under different operational loads and field conditions. This ensures consistent energy efficiency for extended usage.In addition to functional tests, unit testing includes negative test cases where invalid inputs, such as corrupted image data or signal loss, are introduced. These tests help validate the system's ability to gracefully handle unexpected scenarios without system crashes or malfunctions. Unit testing also provides a framework for iterative development. As enhancements or fixes are made to the YOLO model, Arduino code, or hardware, updated tests validate the changes, ensuring new features are integrated without impacting existing functionality. This iterative approach builds a solid foundation for the system's overall reliability.

5.4 INTEGRATION TESTING

Integration testing ensures that all modules within the Weed Eliminator AI system work seamlessly together. It begins with testing individual pairings of modules, such as the camera and YOLO model, to verify that captured images are transmitted correctly and processed accurately. A critical aspect of integration testing involves validating the communication pipeline between the YOLO model and Arduino microcontroller. Testing ensures that detection outputs from the model translate into accurate motor and sprayer commands, minimizing latency and ensuring real-time operation. Further testing focuses on hardware-software integration, such as ensuring the Arduino reliably triggers the 12V DC motor and sprayer nozzle based on YOLO's detection results. This testing is conducted under simulated field conditions to replicate real-world weed densities and random distribution patterns.

Battery integration is another focus area. Tests validate that the battery can provide stable power to all components, including the camera, Arduino, and motor, under varying operational loads. These tests identify potential bottlenecks or power delivery issues that could impact the system's performance during extended usage.Integration testing also involves end-to-end validation of the system. This includes running the YOLO model on a laptop, capturing images via the camera, processing detections, and verifying that the motor activates the sprayer at precise locations. Multiple test cases are crafted to evaluate performance across different field setups, weed densities, and environmental conditions.Lastly, external dependencies, such as the laptop running the YOLO model and its communication with Arduino, are tested. This ensures that all data transfers, including command signals, occur seamlessly without delays or packet losses. By addressing these integration aspects, the Weed Eliminator AI system is validated for real-world functionality and operational readiness.

5.5 REGRESSION TESTING

Regression testing ensures the Weed Eliminator AI system remains stable and reliable as it evolves. When updates are made, such as refining the YOLO model for better weed identification or optimizing Arduino's control logic for faster response times, regression tests are run to confirm that existing functionalities remain unaffected. Test suites cover all previously implemented features, from weed detection accuracy to motor and sprayer operations. Any inconsistencies or failures in these areas signal regressions that are promptly addressed to prevent them from impacting real-world performance. Regression testing extends to hardware components as well. For instance, any update to the motor control logic is tested to verify it does not inadvertently alter the motor's behavior, such as delayed responses or incorrect spray durations. Automated testing is a cornerstone of regression testing. Automated scripts run comprehensive test cases on both the YOLO model and Arduino code, enabling quick identification of regressions introduced by new changes. These tests are executed in various simulated and real-world scenarios to ensure reliability.

Another focus area is the communication between the YOLO model and Arduino. Regression tests validate that updates to the YOLO model, such as improved weed detection thresholds, do not disrupt the data exchange or command execution pipeline.Regression testing also includes battery performance and system durability checks. Updates to any component are tested to confirm they do not increase power consumption unnecessarily or compromise the system's long-term operational stability. This ensures the system remains efficient and sustainable even as new features are added.

5.6 PERFORMANCE TESTING

Performance testing is critical for ensuring the Weed Eliminator AI system delivers optimal speed, efficiency, and reliability under various conditions. The YOLO model is tested for real-time weed detection, ensuring it processes images with minimal latency to maintain a seamless operation. Stress testing evaluates the system's capability to handle dense weed populations. Simulated scenarios with a high number of weed detections are used to measure the system's response time and ensure the sprayer operates without delays or errors, even in challenging conditions. Battery performance is a significant focus of performance testing. The system is tested for prolonged operations under full load, ensuring the 12V battery provides consistent power to the camera, Arduino, and motor without depleting quickly.

Scalability testing assesses the system's ability to adapt to different farm sizes and complexities. Whether it operates in small gardens or large agricultural fields, the system is tested for consistent performance, ensuring the motor and sprayer remain accurate and responsive across diverse setups. Performance testing also involves evaluating the Arduino's real-time responsiveness. The microcontroller's ability to handle simultaneous inputs from the YOLO model and translate them into precise motor actions is tested under varying conditions. Additionally, environmental stress tests simulate adverse conditions such as high temperatures, dusty environments, and uneven terrain. These tests evaluate the hardware's durability and the system's overall performance, ensuring it remains reliable in real-world agricultural settings. Through rigorous performance testing, the Weed Eliminator AI system is optimized for robust, efficient, and scalable operations.

6. SYSTEM IMPLEMENTATION

6.1 YOLO FOR WEED DETECTION

The YOLO (You Only Look Once) model serves as the backbone of the Weed Eliminator AI system, leveraging deep learning to provide real-time object detection. YOLO's transformer-like architecture is specifically designed to handle the simultaneous detection of multiple objects within images, making it highly efficient for real-time weed detection in agricultural fields. By utilizing pre-trained models or fine-tuning on domain-specific datasets, YOLO empowers the system to identify weeds accurately and distinguish them from crops.

6.1.1 REAL-TIME OBJECT DETECTION

The key strength of YOLO lies in its ability to perform real-time object detection, where the model analyzes an image and predicts the presence of weeds within milliseconds. This capability is crucial in the Weed Eliminator AI system, which must respond quickly to dynamic environmental changes in the field. YOLO's efficiency in detecting weeds allows the system to make decisions rapidly, triggering the 12V DC motor to activate the sprayer only when necessary.

6.2 WEED LOCALIZATION AND CLASSIFICATION

YOLO excels at not only detecting objects but also localizing them within the image by generating bounding boxes around each weed. This feature is critical in the Weed Eliminator AI system, as it allows the system to focus its spraying mechanism only on areas containing weeds. YOLO’s classification capabilities enable it to distinguish between weeds and non-weed objects, ensuring that the system does not waste resources on spraying crops or other non-target areas.

6.3 INTEGRATION OF HARDWARE COMPONENTS

In addition to its AI-driven weed detection capabilities, the Weed Eliminator AI system integrates various hardware components to ensure effective operation in the field. The integration of the ESP32-CAM for image capturing, Arduino for controlling hardware, and the 12V DC motor for activating the spraying mechanism creates a seamless flow between AI decision-making and physical actions.

6.4 REAL-TIME IMAGE CAPTURE AND PROCESSING

The ESP32-CAM is a compact camera module that captures live images of the field, which are then processed by the YOLO model. This hardware component model identifies weeds, the Arduino is responsible for activating the motor, which in turn triggers the sprayer to apply herbicide precisely where it is needed is essential for providing the system with up-to date visual data on the field, enabling it to detect weeds in real-time.

6.5 HARDWARE CONTROL FOR SPRAYING

The Arduino serves as the controller for the entire hardware system, including the 12V DC motor and the spraying mechanism. Once the YOLO model identifies weeds, the Arduino is responsible for activating the motor, which in turn triggers the sprayer to apply herbicide precisely where it is needed, minimizing waste and environmental impact.

7. CONCLUSION

The Weed Eliminator AI system offers a sustainable and efficient solution for weed management in agricultural fields. By integrating advanced AI-based weed detection using YOLO and automating the spraying process with precise hardware components like the ESP32-CAM, Arduino, and 12V DC motor, the system minimizes herbicide usage and ensures targeted, environmentally friendly weed elimination. This data-driven approach provides farmers with real-time insights, enabling them to optimize their weed control practices and reduce unnecessary chemical application. The system's adaptability ensures its relevance in various agricultural environments, continually improving through iterative development, user feedback, and fine-tuning of the YOLO model for better weed identification. As a result, Weed Eliminator AI helps enhance efficiency, reduce costs, and contribute to sustainable farming practices.

Through the development and deployment of this system, we gained valuable insights into the integration of artificial intelligence and hardware in real-world applications. The project highlighted the importance of real-time data processing, precise control mechanisms, and continuous improvement to meet the evolving needs of modern agriculture.

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INVESTIGATING THEMATIC ISSUES IN THE NOVEL WEDDING OF ALZAINBY AL-TAYEBSALIH

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DOI: 10.5958/2249-7137.2025.00029.5

ABSTRACT

The current study was carried out in University of Kordofan at Faculty of Arts. Department of English Language and Literature, during the study period 2018-2025. The study title is Thematic Issues in thenovel Wedding of Al- Zain. The descriptive and deductive methods were followed to interpret the data. The primary data were collected through questionaire, books, magazines and Broadcasting Comprehensive sampling was used to select the educators in Bara and Shikan locality those are interested in the novel Wedding of Zain. The population number is 300 readers. Therandom sample size was 47 respondents. The data of the questionnaire were analysed by SPSS (Statistical Package for Social Science). The study answer of the following problem: Why TayebSalih used the contradictory issues in the novel Wedding of Zain. The study results demonstrated the hypotheses. The result explained, 34% were not sure that, there is loss in the flat back of Al-TayebSalih's Occipital brain (immagination lobe). The result showed, 51.1% agreed that Al-TayebSalih is Al-Zain actually nature and behavior. 40.4% agreed that Mousa is a slave that shows the theme of race. And 48,9% also agreed with the wedding's theme, that it was though people had been expectingthe news of Nimaa's wedding, this displays the theme of wedding. Also, 40,4% are agree with Nimaa took Al-Zain as a slave after 75,5% agree Haj Ibrahim paid the dowry ., 48,8% of the respondents agreed with Al-Za'm spreads love in the girls sights. Finally, 34% weren't sure when, why and how TaherRawasy, Abadal-Hafeez, and Abdul Samad also Saeed come to the door of Saeed the Idiot's. 34% aren't sure about the lack of life characteristics and place and time shifting of two sceneries happen together. In conclusion, the study gives suggestions for readers and researchers a light about the dervish and his way of living. The research conductor suggests that researchers should try their best in the root of the word (marriage): it comes from African (Marry). In addition the word (Wedding): Comes from the Arabic stem /wedi/.The study recommended that, the novel wedding of Al-Zain should be considered facts and evidences about Al-Tayeb. Salih and his presence among his people in the *village and other recommendation, the dealers of Arts should concentrate on the loss of the brain which it explains TayebSalih cannot write fictions literature.*

KEYWORDS: *Therandom, Literature, Interpret, Concentrate.*

1. INTRODUCTION

There is one between truth and false hood of the principles of TayebSalih's realistic interactions of his interdependent component parts name and nature in the scope of his novel's characters.The sexism, Traditionalism, Existentialism, Sufism, Christian theism and surrealism forms the different functions of the themes i.e. wedding, dogma, tradition, love, race, superstition , goodness, wisdom and race in thenovel's seat of wedding of Zain, Al-Zain cannot be the individual human moral agent, for what he does to the beautiful women, he cannot have absolute control of his self. However, the theme of tradition is an essential ingredient in wedding of Zain of the human morals in the village.

2-Statement of the Problem

This study attempts to reveal, why Al-TayebSalih used the contradictory issues?. Considering all the contradiction issues in wedding of Zain it appears difficult to consider which is the main theme. Again, the wedding of Zain is neither equivalent nor established work of arts.

3-Objectives of the Study

To give facts that there remain equilibrium between the two substances EL-Zain and Al-TayebSalih.

To share the knowledge of the main themes in wedding of Zain i.e. race, superstition, goodness, dogma, wisdom, wedding love and tradition.

To make modernism and not- modernism is necessarily false with the contradiction, existentialism, realism and surrealism had been identifying the plot of wedding of Zain.

4-.Material and Methods

This study is conducted in University of Kordofan Faculty of Arts Department of English language and Literature, during the period November 2018-2024.

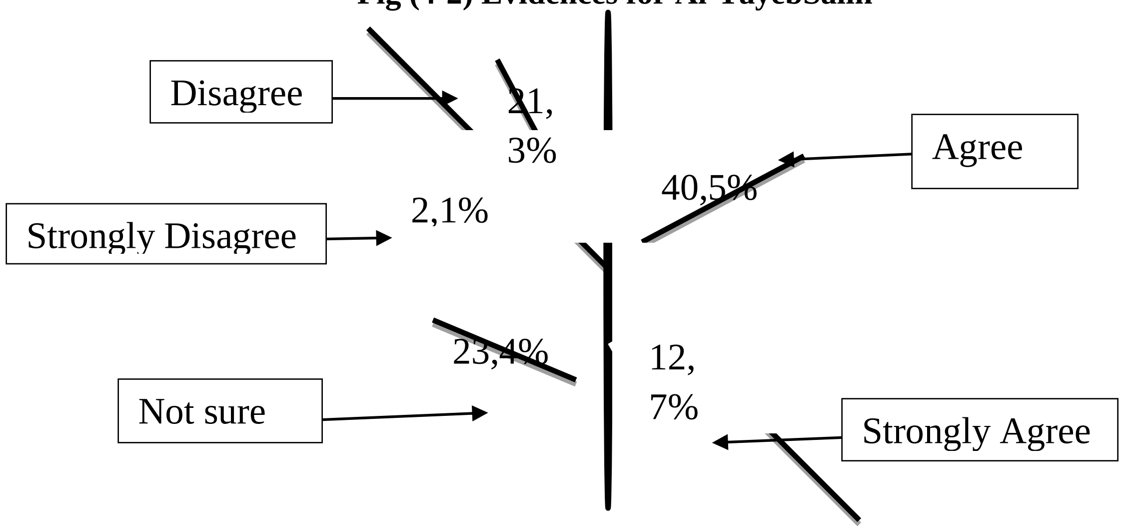
This study justifies El-TayebSalih's several ways of Arts practicing. It indicates clearly, how TayebSalih's life needs studies and researches. This enriches the autobiographical and philosophical approach with scientific instruments, which it accomplished the needs for scientific and philosophical studies on TayebSelih's life. And finally, the lack of information and the need for this study add and presenting evidences of heavy weight, also it is supporting other research conductors and students, libraries and teachers, magazines of Arts and it is adding value to the findings of literature genre.

5-Data Analysis an Discussion

TABLE(-2) EVIDENCES FOR AL-TAYEBSALIH

Options	"Frequency	Percentage
Strongly Agree	06	12,7%
Agree	19	40,5%
Not Sure	11	23,4%
Disagree	10	21,3%
Strongly Disagree	01	2.1%
Total	47	100%

Fig (4-2) Evidences for Al-TayebSalih



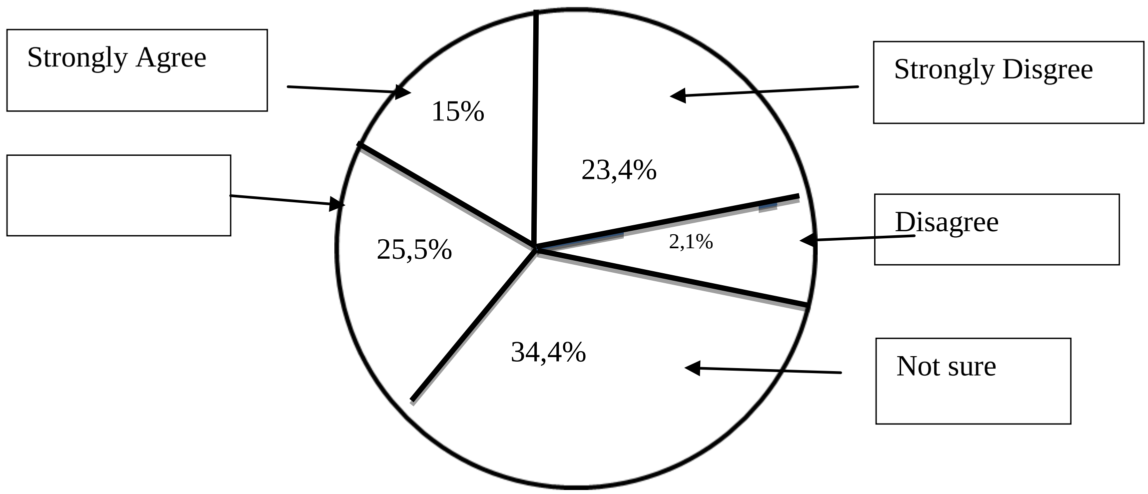
From figure and table (4-2) evidences for Al-TayebSalih, are not in record to make fats about him in the village near Karamakal. Samples responses on statement(2) (47) (100%) responses.(6) respondents strongly agree to the evidences are not in record (12,7%). At the same statement, there are (19), (40,5%) responses are agree with the statement. Also, there are(11) (%23, 4) responses are not sure. There are (10) (21,3%) responses disagree with the statement and(10),(2,1%) responses disagree at the same statement. According to the result, the agreement is high.

Statement (3) Flat Back of the Head. There is loss in the brain (Imagination system) of Al-TayebSelih in his flat back of the head (occipital lobe) 34%.

TABLE (4-3) FLAT BACK OF THE HEAD

Options	"Frequency	Percentage
Strongly Agree	07	15,0%
Agree	12	25,5%
Not Sure	16	34,0%
Disagree	11	23,4%
Strongly Disagree	01	2,1%
Total	47	100%

Fig (4-3) Flat Back of the Head



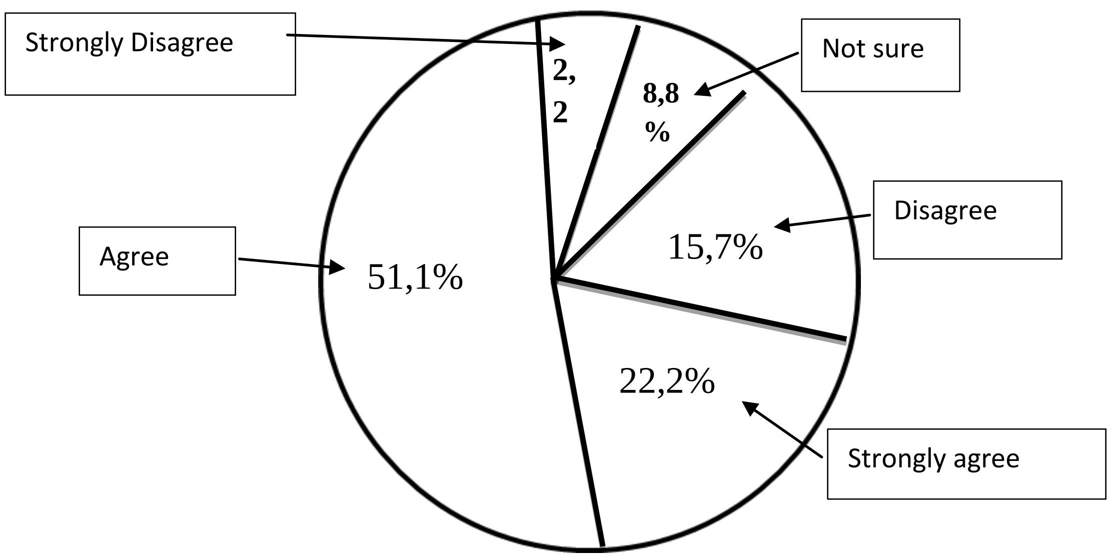
From figure and table (4-3) Flat Back of the Head. There is loss in the brain (Imagination area) of Al-TayebSalih in his flat back of the head (Occipital lobe) 34% - Samples response on statement (3) (47) 100% responses. 7(15%) are strongly agree with the statement. Also, there are 12 (25,5%). agree responses. And 16 (34%) responses are not sure.Thereare11(23,4%) responses disagree and 1 (2,1%) is strongly disagree with the statement. According to the result, The not sure is high (34%) responses.

Statement (4) Al-Zain'sAlayeb, Al-TayebSalih's nature and behavior viewed by Al-Zain, AL.TayebSalih is AL-Zain actually (51,1%).

TABLE (4-4) AL-ZAIN'S AL-TAYEBSALIH

Options	"Frequency	Percentage
Strongly Agree	10	12,7%
Agree	23	40,5%
Not Sure	04	23,4%
Disagree	07	21,3%
Strongly Disagree	01	2.1%
Total	47	100%

Fig (4-4) Al-Zain is Al-TayebSalih



From figure and table (4-4) Al-Zain is Al-TayebSalih. Al-Zain viewed (Al-TayebSalih's nature and behaviour, Al-Tayeb is Al-Zain actually, Samples responses on statement.(4) are: 10 (22,2%) are strongly agree with the statement. And 23 (51,1%) responses are agree, 4(8,8%) are not sure.7(15,7%) responses are disagree. Also,(22,2%) responses is strongly disagree with the statement. According to the result of agree is high (51,1%).

Statement (5) Christian Divorce.Saeed the Idiot's wife wanted to divorce Saeed, that had been associated with Christian divorce (44,7%).

6-CONCLUSION

This summer views the thematic issueusabilityproceeding from the historical account of the auther and his philosophies in the seats of Wedding of Zain's novel. The first chapter, which it expresses the problem of the research and the contradictory issues in Wedding of Zain's novel.

The objectives of the study were doneaccording to the hypothesis by the researcher and answer the research questions to achieve and confirm the objectives of this research and to confirm the hypothesis of the study because of this study importance and it significance in the Arts practising. The study method is through the descriptive analytical method approach during the study period (November 2018).

7-Recommendations

The The morphology appearence of Al-TayebSalih should be without

regard to the presence of the novel study. And Moreover, the morphologicalappearance

Of his Occipital lobe should be regarded a small size and flat lobe, which it provides less-work in the imagination. The structure of his brain should be put into account when the autherised dealers of Arts come to form and organise the masterpieces of Artistic works. Meanwhile, Al-TayebSalih's Award for the art should be eventually changed into another labelling.

The novel Wedding of Zain, shouldn't beatergorised under the literary works in the domain of literature, for the loss of the brain brain in Al-TayebSalih's head's size.

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SAFEGUARD WILD: ANTI-POACHING MONITORING SYSTEM USING ML & IOT

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DOI: 10.5958/2249-7137.2025.00030.6

ABSTRACT

The danger to wildlife due to illegal poaching activities has increased over the past few years, and there is a pressing need for creative solutions to safeguard threatened species. To address this, we propose an Anti-Poaching System Using IoT as an integrated model to track, identify, and deter illegal activities in forest and protected areas. By using networked IoT sensors, the system facilitates real-time identification of human activity, strange noises like gunshot and fire thread. It provides warning messages to forest departments in real time in the form of message ,live video feed and image ,facilitating quick action. This combined solution equips authorities with smart surveillance, automated threat identification, and instant reporting leveraging wildlife conservation efforts and reducing human-wildlife conflict through timely intervention. Our dream is to implement this in national parks and reserves.

KEYWORDS: *Anti-Poaching, Wildlife Monitoring, Ky-037 Sensor ,Flamesensors,Raspberry Pi 3B+ ,Ultrasonic Sensor ,Webcam, Servo Motor Tracking ,YOLO Object Detection, Edge Computing ,Remote Monitoring, Telegram Alerts.*

1. INTRODUCTION

Wildlife poaching continues to be one of the most serious threats to biodiversity, driving a number of species to the brink of extinction. Conventional patrolling and monitoring techniques tend to fail in monitoring extensive forest cover and identifying poaching in real time. To meet this challenge, the "Safe Guard Wild: Anti-Poaching Monitoring System Using IoT" project presents an intelligent, automated solution that leverages artificial intelligence, computer vision, and IoT technologies to protect wildlife.This implementation makes use of a Raspberry Pi 3B+ as the processing core, connected with a servo-mounted ultrasonic sensor for motion detection and a YOLO-based object detection model for real-time detection of animals, poachers, and weapons. It has a Tkinter-based GUI for local monitoring and control purposes, while vital alerts and captured images are sent instantly through Telegram to authorized forest staff. The system also keeps track of all occurrences in an SQLite database for future reporting and analysis.

2. Related Work

In the last decade, scientists and conservationists have investigated a range of technological solutions to meet the increasing threat of wildlife poaching. Conventional methods like patrolling manually and using camera traps have been extensively used. The recent evolution has incorporated the use of Internet of Things (IoT) devices and Artificial Intelligence (AI) in conservation efforts. Concurrently, real-time monitoring systems employing drones, thermal sensors, and acoustic sensors have been established to alert for human entry or gunfire in protected areas. Other research has even targeted edge computing platforms, including the Raspberry Pi, to support local data processing and minimize the reliance on cloud services in off-grid areas.In addition, the utilization of messaging platforms like Twilio and Telegram in warning rangers has been promising in mitigating the response time. Database-driven logging systems have been used in certain systems to enable long-term monitoring, reporting, and pattern analysis. This project draws on such previous work by developing a cost-effective, Raspberry Pi-powered system that integrates YOLO object detection, servo-driven ultrasonic sensing, real-time notifications, and GUI-driven local monitoringall for the sake of providing an implementable and deployable solution for wildlife conservation.

3. Methodology

3.1 System Architecture

Anti-Poaching Monitoring System includes four major components: sensing unit, processing unit, communication unit, and alert system. The sensing unit consists of sound sensor ,flame sensor and optional cameras.The sensor detect the frequency of the sound and mic receives the sound and detect the unusual sounds and the camera detect the illegal entry of persons. The processing unit is the microcontroller, which receives signals from the sensors. It processes this data to check whether there is gunshot or poaching.

3.1.1 Hardware Architecture

The architecture of the wildlife conservation system consists of four layers. The Sensor Layer consists of sound sensors (KY-037) that sense gunshots, flame sensors to sense fire, and cameras for visual monitoring, sensing data from the environment continuously. The Processing Layer processes the data with a Raspberry Pi or equivalent, using machine learning algorithms such as TensorFlow Lite to sense gunshots and YOLO to sense wildlife and poachers. The Communication Layer provides IoT-based communication, sending notifications and alerts to the system. Finally, the User Interface Layer, deployed with Tkinter, gives a graphical interface for users to view the system, be alerted, and view historical data.

3.2 Software Architecture

The software architecture of the system is based on a Linux operating system (e.g., Raspbian) on the Raspberry Pi with the necessary libraries and frameworks. The core libraries used are OpenCV for object detection and image processing, TensorFlow Lite for running the machine learning model for voice analysis, Librosa for audio feature extraction, and Requests for notification of alerts via Telegram. Tkinter is used for creating the system's user interface with real-time monitoring, alert logs, and system control. SQLite database is used for storing history data of alerts and detections such that previous events can be accessed and tracked efficiently.

3.3SystemIntegration and Communication

It combines different hardware and software elements to ensure effective communication and threat detection. Raspberry Pi is connected to sensors such as sound and flame sensors, which offer real-time information, which is processed by machine learning algorithms for audio analysis and object recognition. On threat detection, the system alerts via Telegram with location and time stamp information. Real-time sensor readings, system status, and alert history are displayed by the user interface using Tkinter, enabling rapid monitoring and response. The combination of all the components enables timely detection of threats and increases wildlife conservation.

3.4 Scalability and Modularity

The Anti-Poaching Monitoring System is designed in modularity and scalability towards future growth and development to maintain pace with evolving conservation requirements. Every component—i.e., sensors, processing, and communication interfaces—can be individually developed, tested, and upgraded in modular form. The modularity facilitates the addition of new sensors or cameras to enhance the monitoring capability without significant change in the current system.

4. PROPOSED SYSTEM

4.1 Selected Methodology/Process Model

Working Principle:

The Safe Guard Wild Anti-Poaching Monitoring System operates by deploying a network of IoT devices like cameras, motion sensors, sound sensors, and environmental sensors over a wildlife sanctuary. The devices continuously scan the environment for any suspicious activity like poacher movement, animal distress signals, or gun sounds. The system employs AI models trained to detect animal species, detect poachers, and detect gun sounds. Images and sensor data are processed locally on edge devices like Raspberry Pi, which aids in low latency. Once suspicious activity is detected, real-time alerts are sent via Telegram or SMS to rangers or park authorities to respond in real-time. The system is designed to operate independently, enabling 24/7 monitoring and reducing risk to wildlife as well as park officials.

Hardware Assembly: Connect USB Camera,Microphone Module, ultrasonic sensor,Sound Sensor(KY-037) ,Flame Sensor, Servo Motor andRaspberry Pi 3 Model B+.

Software Setup: Install necessary libraries for sensor, camera

Sensor Calibration: Calibrate the ultrasonic sensors to accurately detect distances.

Image and Data Capture: Record environment images and sensor data.

Sound Detection: Process sensor readings to identify the unusual sound.

Real time Alerts : Provide real time alert message to smart phone.

Testing and Validation: Ensure system accuracy and reliability in real-world environments.

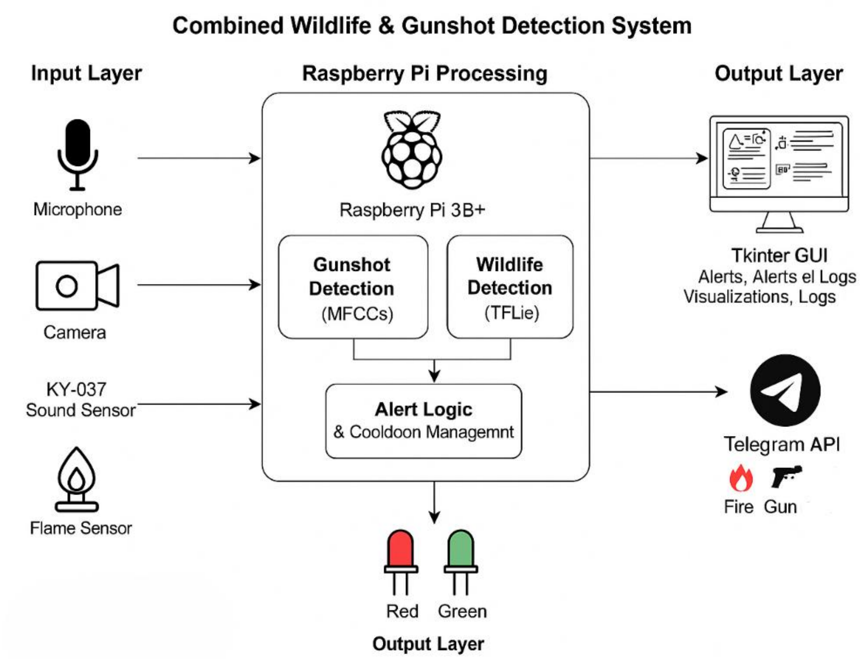
5. AI Model Design and Training

Combines computer vision and audio classification to identify wildlife, poachers, and gunshots in real-time. A YOLO object detection model trained on self-labeled datasets is used to identify animals, guns, and humans (poachers/rangers) from camera streams, while a CNN-based audio classification model analyzes audio spectrograms to identify and classify gunshots. Both models are trained on optimized datasets with data augmentation, validated on unseen data, and implemented in lightweight versions which can be run on Raspberry Pi. These AI modules provide continuous monitoring and real-time alerting for suspected poaching activity.

5.1 Model Architecture

The model design integrates a YOLO (You Only Look Once) convolutional neural network for real-time object detection and a 1D or 2D CNN-based audio classifier for gunshot noise detection. YOLO takes image frames from the camera and applies multiple layers of convolutional layers to detect and classify animals, poachers, and guns with high speed and accuracy. The audio model translates recorded audio into spectrograms, which are passed through a CNN to identify and classify gunshot noise. Both models are edge-optimized and

lightweight for deployment on a Raspberry Pi to function efficiently and react appropriately in field environments.



5.2 Dataset Preparation and Preprocessing

The AI model is trained on:

Custom Dataset: Captured using webcam in real-world environments, i.e., indoor and outdoor environments.Open Datasets: Augmented with small-scale pedestrian and obstacle detection datasets.

Preprocessing includes:

Scaling images to fit webcam inputs (e.g., 640x450 pixel).Data augmentation (rotation, flip) for better generalization.Audio recordings were transformed into mel-spectrograms to obtain sound frequencies over time.

5.3 Feature Engineering

Critical characteristics derived for improved obstacle detection:

Edge Detection: identification of prominent patterns from visual and auditory input. Object edges, shapes, and textures were automatically learned as features in image inputs using convolutional layers in the YOLO architecture. In audio detection, time-frequency features were extracted from mel-spectrograms, which possessed unique gunshot signatures.

5.4 Training and Optimization

Training: Both YOLO object detection model and sound detection model were trained separately on their own datasets. The YOLO model was trained on wildlife images with labels, whereas the sound detection model was trained on audio data with gunshot and non-gunshot samples.

Optimization: Hyperparameters like learning rate, batch size, and optimizer selection were optimized for the models.Model performance was validated with validation data and optimized by making iterative adjustments.

Early Stopping: Prevents overfitting during training.

5.5 Model Deployment and Inference

After training:

Post-optimization and training, the YOLO model is converted to NCNN and sound detection were deployed on the Raspberry Pi 3B+ with Edge Impulse to perform inference in real time with efficiency. The models were integrated into the IoT-based system for monitoring wildlife poaching and libraries and frameworks for running models locally were installed. The two models alert the monitoring system or control center in the event of suspicious activity, which triggers further action such as alerts or automated response.

5.6 Continuous Improvement:

The system is designed for ongoing improvement of performance. With fresh data collected through wildlife monitoring and environmental conditions, the models can be retrained and updated to increase accuracy and responsiveness. Regular updates to the training dataset and model parameter optimization enable the system to effectively respond to changing conditions and new threats.

5.7 Performance Benchmarking

Accuracy: 75%–85% for common indoor/outdoor obstacles.

Inference Speed: Average detection time under 200ms per frame.

Model Size: Less than 500KB, optimized for webcam and microphone

False Alerts: Maintained below 5% through threshold tuning and sensor fusion.

6. Methodology

The System was designed and developed with an iterative and systematic process emphasizing real-time performance, resource limitation, and usability by blind users. The methodology was broken down into five phases: Requirement Analysis, Design and Development, Model Training, System Integration, and Evaluation. A consideration of what can be done on a system with real-time performance, restricted hardware resources, and efficiency accompanied the activity in each phase.

6.1 Phase I: Requirement Analysis

The initial phase was to identify the particular requirements of visually impaired users and study the requirements for real-time obstacle detection and navigation guidance. Major findings were The requirement for a light system that works well on low-power devices such as the Camera,The need for real-time feedback, so the system can guide users immediately when obstacles are encountered.The system should be accurate, with clear and consistent audio cues for navigation.A requirement specification was created based on these findings, with an emphasis on Real-time obstacle detection and navigation guidance.Lightweight architecture for the Camera platform.

6.2 Phase II: Design and Development

Hardware Platform: The right IoT sensors, cameras, and microphones are selected based on the requirements of the area to be monitored. These are connected to the Raspberry Pi, and required communications protocols such as MQTT and HTTP are configured to export sensor data in real-time.

AI Model Integration: The sound classification (for gunshot detection) and object detection (YOLO) AI models are integrated on the Raspberry Pi. This entails converting the models to real-time inference and optimization to the Raspberry Pi's low computational capabilities.

6.3 Phase III: Model Training

Training of the AI model was a critical phase of ensuring accurate and efficient object recognition and sound classification. Training entailed:

Dataset Acquisition: Training of the model begins with the acquisition of a comprehensive dataset. In this project, they are images of wildlife animals, poachers, and weapons inside wildlife sanctuaries and audio recordings of gunshots or any other suspicious sound. The dataset can be augmented with existing datasets and supplemented by sensor readings (distance, angle) from IoT sensors to make the model more accurate and robust.

Data Preprocessing: Image resizing, augmentation (rotation, flipping), and normalization were applied to prepare the data for model training.

Model Selection: Model selection varies based on task and data type. For image data, the pre-trained convolutional neural network (CNN) model, e.g., YOLO (You Only Look Once), is utilized for object detection tasks like weapon, animal, and poacher detection. For sound classification, an audio-based deep learning model, e.g., convolutional neural network (CNN) or recurrent neural network (RNN), is used to classify the gunshots.

Training Strategy: Data augmentation to obtain the most diverse set of data possible by using methods like rotation, scaling, and noise injection is part of the training strategy, and transfer learning to utilize pre-trained models (e.g., YOLO for object detection or CNNs for audio classification) to hasten convergence and enhance performance. Learning rate, batch size, and optimizer are all initialized as hyperparameters to maximize the model's efficiency and cross-validation to prevent overfitting and generalization.

6.4 Phase IV: System Integration

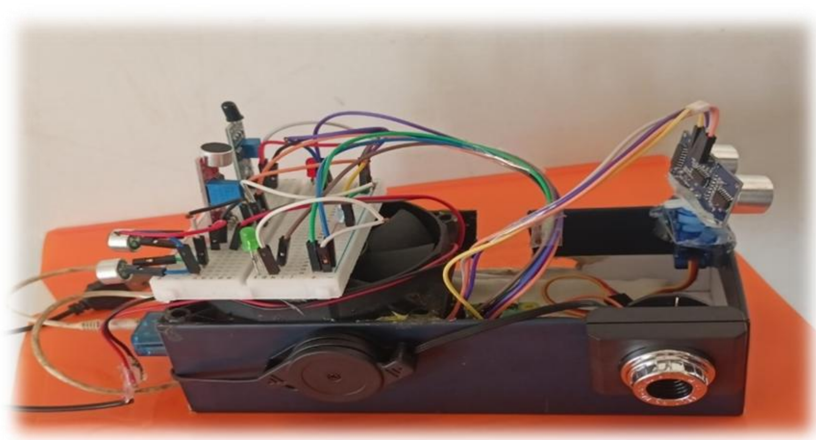
System integration is the process of integrating all the parts of the anti-poaching monitoring system as a functional unit. This is the process of integrating AI models for image and audio recognition, sensor inputs from ultrasonic sensors and cameras, and communication modules (e.g., Twilio, Telegram) for real-time alerts. The AI models run on the Raspberry Pi, which communicates with sensors and processes the incoming data. The system also incorporates a user-friendly GUI for easy monitoring and control. All the parts, including the database to store animal sightings, alerts, and sensor data, are networked together to facilitate seamless interaction between hardware, software, and communication systems to facilitate real-time monitoring and timely alerts for poaching.

6.5 Phase V: Evaluation

Evaluating its performance on major parameters like accuracy, false alarm rate, and response time. The object detection and sound classification machine learning models are tested on how well they can detect animals, poachers, and gunshots correctly with a minimum accuracy of 75-85%. The system's capability to reduce false alarms is of paramount importance for field deployment, with the objective of keeping the false alarm rate low as well as providing timely and correct alerts. The system's responsiveness, environmental robustness, and sensor integration are also tested in real-time environments to ensure field reliability.

7. Applications and Future Work

Safe Guard Wild Anti-Poaching Monitoring System are far-reaching and encompass wildlife conservation, environmental protection, and law enforcement, as well as enhancing safety in national parks and wildlife reserves. Using IoT, AI, and real-time monitoring, the system presents a viable solution for the detection of poaching activity, enabling rapid intervention. Future work entails refining the accuracy of the models, creating more capabilities in the sensors, and incorporating more advanced AI algorithms for enhanced object detection and sound classification.



7.1 Application

7.1.1 Wildlife Poaching Detection and Prevention

The first application of this system is the detection and prevention of poaching in forests and wildlife sanctuaries. The system is supported by motion sensors, sound sensors, and cameras in detecting abnormal movement or sound like gunfire, footsteps, or engine revving. Machine learning algorithms process this data in real time to recognize it as possible poaching activity. Officials are notified in real time, enabling rapid response and minimal risk of damage to wildlife.

7.1.2 Real-Time Monitoring of Protected Areas

This system allows for the surveillance of forest areas under coverage 24/7 without relying on round-the-clock human labor. IoT sensors sweep the area in real time and feed it to the central server or cloud platform. Real-time dashboards deliver real-time feeds, alerts, and analytics by which authorities can track vast expanses of land and respond to threats in a timely manner.

7.1.3 Remote Surveillance in Conservation Areas

With autonomous capabilities and IoT connectivity, the system enables real-time monitoring of remote and inaccessible locations. It reduces the requirement for constant patrolling, saving human efforts and providing better coverage over large forest regions.

7.1.4 Smart Border Monitoring

In global border wildlife sanctuaries, the system not only identifies poaching but also cross-border illegal wildlife trade. Human classification using AI distinguishes human entities from animals (rangers/poachers) and from one another based on situational awareness.

7.1.5 Early Warning Systems for Villages near Forests

Villages residing close to the habitat of wildlife are usually prone to invasions by wild animals. This system will be capable of warning villagers in advance regarding animal movement in the area so that villagers will be prepared and won't encounter conflict.

7.2 Future Work

While the Safe Guard Wild Anti-Poaching Monitoring System has proven useful, there are numerous avenues for future work and enhancement to expand its capabilities, improve its accuracy, and increase its potential for real-world application.

7.2.1 Enhanced Sensor Integration and Miniaturization

Future advancements in IoT-based anti-poaching technology will include the incorporation of more sophisticated and miniaturized sensors that can be subtly integrated into animal collars, trees, or underground. The sensors will be ultra-low-power thermal imaging cameras, vibration sensors, and acoustic sensors that can distinguish between human movement and natural wildlife movement. Multi-spectral imaging will be employed to enhance species identification, with environmental sensors monitoring habitat conditions. Additionally, bio-inspired structures such as camouflage coatings and self-cleaning systems will enable long-term operation in harsh wilderness conditions without alerting poachers.

7.2.2 AI and Machine Learning Advancements

Artificial intelligence will be critical in mapping raw sensor data into actionable insights. Future systems will employ deep learning architectures to analyze wildlife and poacher behavior patterns in support of predictive threat notification. Edge AI will allow on-the-edge processing on low-power hardware, minimizing the dependency on cloud computing and allowing for faster reaction times. All of these technologies will make anti-poaching systems more intelligent, more dynamic, and capable of learning from evolving poaching tactics.

7.2.3 Autonomous Monitoring Systems

The next-generation anti-poaching technology will employ autonomous robots and drone systems for wide-area, real-time surveillance. AI-driven swarms of drones will blanket high-risk zones with optimal flight trajectories, while silent drive technology will be inaudible to poachers. IoT underwater sensors and autonomous subs will blanket oceanic zones, monitoring illegal fishing vessels and tracking threatened sea species. Renewable-powered charging stations along remote roads will supply a continuous power source, rendering the systems autonomous even in the most remote areas.

7.2.4 Advanced Communication Networks

Having a solid communication line is paramount in remote wilderness regions. Next-generation systems will integrate LoRaWAN, satellite communication, and mesh networks to make data transfer a seamless process. Delay-tolerant networking (DTN) protocols will buffer and relay data during low-connectivity situations. In the future, quantum communication might offer ultra-secure, tamper-free data transfer, whereby it would not be feasible for poachers to jam or intercept signals. Hybrid networks will offer rangers real-time alerts even in extreme environments.

7.2.5 Blockchain for Conservation

Blockchain technology will improve accountability and transparency in anti-poaching operations. Indelible records of sensor data will be used as admissible evidence during prosecution of poachers, and smart contracts will be used to automate deployment of rangers and resource allocation. Blockchain tracing of supply chains will also enable tracing of illegal wildlife products from origin to market, disrupting trafficking chains. Tokenized reward schemes could also motivate local communities to report poaching activity, with improved cooperation in conservation.

7.2.6 Human-Centric Design and Community Integration

For IoT anti-poaching solutions to succeed, they have to involve the local communities. Future innovation will be in user-friendly mobile apps that will enable villagers to report suspicious activity with ease. Training procedures will train rangers to fix and maintain IoT devices, and culturally adapted alert systems will enable ease of use in various areas. Blending local tradition and indigenous knowledge, the systems will build trust and long-term collaboration among conservationists and communities.

7.2.7 Energy Harvesting and Sustainability

Since the majority of wildlife locations do not have a reliable power source, next-generation IoT devices will need to be self-sustaining. Solar, kinetic, and bio-energy harvesting technologies will energize sensors for years without battery replacement. Self-healing materials and energy-efficient networking protocols will also enhance longevity. Experimental concepts such as plant-powered bio-batteries could even allow sensors to capture energy from their surroundings, making them completely self-sustain in.

8. CONCLUSION

The Safe Guard anti-poaching monitoring system proposed is a revolutionary wildlife conservation solution, combining the strengths of IoT, AI, and real-time monitoring to tackle the daunting challenge of poaching. With the integration of sound detection and image identification through machine learning models, the system can accurately detect poaching activity with minimal false alarms and send timely notifications to the authorities to respond effectively. With the utilization of a well-structured system architecture, effective model training, and deployment of a variety of sensors, the solution tackles both environmental and operational challenges in the field. The deployment of the system not only guarantees increased monitoring capability but also minimizing the risks in wildlife to illegal activities. Moreover, its flexibility to tackle diverse terrains, coupled with ongoing AI accuracy improvements and system optimization, guarantees long-term system sustainability. In the future, the scalability of the system, the ability to add more sensor technologies, and integration with larger conservation and law enforcement systems will be crucial to further expanding its coverage. Finally, the anti-poaching monitoring system is an innovative solution that can be easily replicated globally to guarantee biodiversity conservation, protection of endangered species, and overall ecosystem health globally.

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