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Research Article

AI-Based Real-Time Detection of Hazardous Fauna and Flora Using YOLO and LLM Integration: A Mobile Application for Muğla Region

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Abstract

In recent years, increased sedentary work and prolonged screen time have led people to lead sedentary lifestyles and reduced opportunities for interaction with nature. While interest in outdoor activities such as hiking, camping, and mushroom picking has increased, the rapid and accurate identification of animals and plants encountered in nature remains a critical need. During increasingly popular nature walks, there is a risk of encountering wild or poisonous species for uninformed participants. In this study, an AI-powered mobile application was developed for the automatic detection and identification of frequently encountered animal and plant species in the Muğla region. The system detects species using YOLOv11n models trained on publicly available datasets and datasets created with tags, and determines biological information, agricultural impacts, and human interaction risks specific to the detected organism using Grow and Llama-4-Scout. The results show that the system provides high accuracy across different datasets; mAP@0.5 values were measured as 0.801, 0.889, 0.964, and 0.908. This approach provides a practical and accessible solution that supports users in interacting safely in nature. The information generated by the LLM was evaluated against predefined baseline facts using BLEU, ROUGE, METEOR, and BERT Score metrics. The system aims to enhance user safety by providing real-time information, particularly regarding hazardous species.

Keywords: Artificial Intelligence; Large Language Model (LLM); Object Detection; YOLO; Mobile Application.

Introduction

Today, the habits brought about by technology and urban life have significantly reduced individuals' interaction with nature. The intensive use of digital devices and the rapid increase in urbanization are causing people to move away from physical activities and weaken their contact with the natural environment. However, accurate and timely identification of animal and plant species is of great importance in areas such as increasing agricultural productivity, early diagnosis of plant diseases, conservation of biodiversity and ecosystem management [1-5]. In this regard, artificial intelligence and deep learning-based image processing technologies

have yielded effective results with high accuracy rates in the detection and classification of both plant and animal species in recent years [1-10]. These technological developments pave the way for innovative solutions that integrate nature and the digital world, contributing to sustainable environmental management and the conservation of biodiversity [10,11]. Recent advances in computer vision and deep learning, particularly Convolutional Neural Networks (CNNs) and YOLO (YouTube) Only Look Architectures such as YOLO have revolutionized automated species recognition from images [1–4,12]. Models such as Reset, Mobile Net, Mobile ViT, and Efficient Net have demonstrated high accuracy in detecting and classifying different organisms in various environments [2,4,6–9,13–15]. They have often enabled real-time processing, even on resource-constrained mobile or edge devices. These technologies facilitate applications such as automated wildlife monitoring, farm safety, plant disease diagnosis, maturity assessment, and medicinal plant identification. Many systems utilize transfer learning and data augmentation techniques to cope with limited or unstable data and integrate mobile applications or APIs for improved usability.

Despite these significant advances, challenges remain in developing robust systems that can accurately identify a wide range of species (both fauna and flora) under varying conditions, handle small or remote targets, and provide users with reliable, contextual information beyond simple classification [1,12,13]. Furthermore, while Large Language Models (LLMs) offer great potential for generating descriptive information, effectively integrating them into automated identification workflows and evaluating the quality of their outputs is still an area to be explored [10]. This project is built upon four separate, customized datasets for identifying different animal and plant species. The first animal dataset includes the Ankara goat, wild goat, and other goat breeds; the second covers arthropods and small insect species, including the Mediterranean recluse spider, the Anatolian yellow scorpion, and fruit fly species. The first plant dataset includes fungal species such as the common mushroom, button mushroom, chanterelle mushroom, and fly agaric. The second includes various flower and plant species such as sage, bellflower, and thyme.

For each dataset, custom YOLOv11n models were developed based on detailed visual representations of the relevant species, and model weights were recorded to ensure the highest accuracy performance. Datasets were generated through manual image collection from the internet, integration of publicly available datasets (e.g., Rob flow), and semi-automatic labeling processes. Data enhancement techniques were applied using the Augmentations library to reduce class imbalance and increase data diversity. The resulting models are able to detect and classify species in uploaded images according to the highest confidence score.

aims to perform species detection by processing images provided by users via a Flutter mobile application. The images are sent to YOLOv11n models, which run on a Fast API backend and are trained separately for different species. The model identifies the species with the highest confidence score above a defined threshold. Detailed information about the detected species is generated in Turkish by the LLM, and the resulting text is quantitatively evaluated using BLEU, ROUGE, METEOR, and BERT Score metrics by comparing it with the reference dataset. The results are stored on Firebase, and detection details, input images, and metric evaluation graphs are presented in Hugging. Face It is archived in the dataset repository.

This approach offers an end-to-end system that integrates the identification of different animal and plant species with LLM-based knowledge generation. The system, developed using augmented and multi-source datasets, YOLOv11n models, quantitative evaluation of LLM outputs with standard text similarity metrics, and the integration of a mobile front-end and API back-end, is expected to serve as an effective and practical tool for users in agriculture, citizen science, and education.

The developed ANIPICT system offers an integrated approach that addresses three fundamentals shortcomings in the existing literature: (1) the creation of customized datasets for the local fauna and flora specific to the Muğla region, (2) providing contextual and descriptive information to the user through LLM integration, going beyond object detection, and (3) the development of a hierarchical decision-making mechanism capable of processing both animal and plant/fungus species in real time on a single mobile application. The vast majority of existing studies address these three functions separately; studies that bring them together in an end-to-end mobile system is extremely limited.

Literature Review

In recent years, artificial intelligence and deep learning techniques have led to remarkable advances in fields such as agriculture, plant and fungal species identification, and wildlife monitoring. The development of mobile and web-based systems has made real-time object, plant, and disease identification possible, thus making agricultural production processes, environmental monitoring, and biodiversity conservation activities more efficient and reliable.

Developed by the Minister and his colleagues, the Wildcare -YOLO model offers a lightweight and high-efficiency approach to the recognition of endangered wild animals [1]. The model, Mobile Bottleneck The model reduces computational costs through block modules and an improved Stem Block structure, while increasing accuracy thanks to its Bifans- based neck structure and Focal-Eeyou loss function. Experimental results show a 28.55% reduction in model parameters, a 50.92% reduction in FLOPs, and a 17.65% increase in FPS. However, the model's performance in different weather conditions and low-light environments has not yet been sufficiently tested.

Yılmaz et al. developed a YOLO-based ANFIS-controlled unmanned ground vehicle (UGV) that enables autonomous detection and spraying of diseased plants. When comparing the

YOLOv7, YOLOv8, and YOLOv9 models, YOLOv8 was determined to have the highest accuracy, and its applicability on Raspberry Pi 4B was demonstrated. Equipped with five ultrasonic sensors and an ANFIS-based decision module, the system achieved 79% accuracy in spraying by targeting only diseased areas. This study makes significant contributions to the applicability of low-cost smart agriculture systems in the field [3].

The system developed by Subha and his team provides high accuracy in detecting plant diseases by combining a Mobile ViT- based deep learning model with self-calibrating lighting improvement methods. In addition, it offers immediate preventive measures to the farmer after disease detection using a Dialog flow-based smart chatbot and a Sequence-to-Sequence LSTM model. The system achieved 92% disease detection accuracy, 88% treatment recommendation accuracy and 94% multilingual translation success even under low light conditions [6].

Sharmah et al. developed a user-friendly mobile application in the field of agriculture using ResNet50, VGG16 and InceptionV3 models and classified six different rice leaf diseases. The system, integrated into the Android application via Flask -based REST API, achieved an accuracy rate of 82.9% with the VGG16 model. This study shows that deep learning-based mobile applications can be an effective solution for agricultural disease detection [9].

Omaima and colleagues have developed a mobile and web-based solution called Envi Scan + that successfully identifies plant species with high accuracy using CNN-based models. The system offers plant care suggestions to the user via an integrated chatbot; thanks to its Spring Boot, React and Android- based architecture, it supports sustainable agriculture applications [10].

Yan et al. proposed an algorithm called EA-YOLO for detecting endangered animals. This YOLOv8-based model uses Global Attention. It aimed to address the problems of low accuracy and poor feature extraction with Mechanism (GAM) and multi-scale object detection heads. In tests on the LoTE-Animal dataset, an average improvement of 9% in accuracy was achieved [12].

Nishanth and his team developed the YOLOv10 model with NVIDIA Jetson By running it on a nano, they developed a low-power, real-time wildlife monitoring system. The system detects animals with high accuracy through remote imaging, while being notable for its portability and energy efficiency [13]. Similarly, Krishnaveni et al. designed a smart animal tracking system based on YOLO and OpenCV; this system provides farmers with important behavioral data by monitoring animal activities in real time in farm environments [14].

Gobinath et al. developed a system for the automatic identification of mushroom species using a CNN-based model. The model provides the user with information on mushroom species and edibility while classifying with high accuracy [15].

Chen et al. developed the YOLO-SAG algorithm based on YOLOv8n and integrated the Softplus activation function, AIFI and Gascons modules. This resulted in a 94.9% accuracy rate and an 11.1% reduction in computational load [16].

Bhagabati and his team aimed to reduce human-animal conflicts in Kaziranga National Park with the YOLOv5 model, which they integrated with the Senet attention mechanism. In experiments conducted on a special dataset including species such as elephants, tigers and deer, the system achieved a 96% accuracy rate in day and night conditions [19].

Hruška et al. detected weeds in cabbage fields on RGB and NIR (near infrared) images using the YOLOv8, YOLOv9 and YOLOv10 models. The study proposes the Four-Band Difference Vegetation Index (FBDVI) method and shows that combining RGB+NIR data significantly improves the classification performance. This approach offers significant potential for targeted interventions in precision agriculture applications [17].

Subramani et al. compared SVM, ResNet50, YOLOv5 and Alex Net models for the detection of poisonous mushrooms in the Karnataka region. On a dataset of 620 images, the SVM model was found to have the best performance with an accuracy rate of 83%. The study highlights the limitations of limited datasets and draws attention to the importance of using deep learning methods with increased datasets in the future [21]. Similarly, Gobinath and his team classified mushroom species with a YOLOv5-based system and achieved high success in distinguishing between edible and poisonous [15].

Almasy et al. developed a multi-platform mobile application for fruit and vegetable detection by combining YOLOv5 and Flutter technologies. The system identified 20 different types with 96.7% accuracy and provided real-time healthy consumption recommendations. The Flutter infrastructure made the application accessible for both education and daily use [20].

Vilar-Andreu and his team developed a generalized insect detection system based on YOLOv8 and obtained values of 0.967 mAP@0.5 for the medium model and 0.632 mAP@0.5–0.95 for the large model on the IP102 dataset. These results highlight the effect of dataset diversity on model performance and the importance of real-time pest monitoring systems for sustainable agriculture [18].

As observed in the research, the vast majority of studies focus on a single biological category (only plants, only fungi, or only animals); real-time mobile application integration is rarely included. Furthermore, an approach that supports the findings with LLM-based explanatory information generation and quantitatively evaluates these outputs using standard NLP metrics is not yet widespread in the literature. Table 1 presents the basic features of ANIPICT in a comparative manner with selected relevant studies. The ANIPICT system developed in this context aims to address this gap in the existing literature.

Table 1: Comparative Analysis with Related Studies.

Study	Scope	Mobile Application	LLM Integration	Local Dataset	LLM Metric Value.
Minister et al. [1]	Wild animal	✗	✗	✗	✗
Subha et al. [6]	Plant disease	✓	Partial (chatbot)	✗	✗
Oumaima et al. [10]	Plant species	✓	Partial (chatbot)	✗	✗
Alamsyah et al. [20]	Fruits / vegetables	✓	✗	✗	✗
Subramani et al. [21]	Mushroom	✗	✗	✗	✗
ANIPICT (This study)	Animal + Insect + Plant + Fungus	✓	✓	✓ (Muğla)	✓

Materials And Methods

This section details the datasets, materials, models, and system infrastructure used for the ANIPICT mobile alert system, which uses artificial intelligence to identify insect and plant species in the forests of the Muğla region. The main objective of the study is to collect scientific data by analyzing images of biological species observed in their natural environment and to provide users with rapid feedback in a mobile environment.

Data Se

Training datasets for identifying animal and plant species were created by combining images from multiple sources and applying semi-manual/semi-automatic labeling processes. This process involved downloading images of some species from the internet and labeling them using semi-manual/semi-automatic methods to create our own datasets, while for other datasets, we utilized publicly available datasets on the internet. some species included in the datasets are not geographically specific to the Muğla region, for object detection models to make accurate classifications, the dataset must include not only the target species but also visually similar but distinct species. This approach allows the model to learn morphological differences between potentially confusing species and reduce the false positive rate. For example, the inclusion of breeds such as Ankara goat and Humanly goat in the goat dataset is essential for the model to distinguish wild goat from other goat breeds. Similarly, the species diversity in the insect dataset increases the reliability of interclass differentiation among arthropods. Therefore, the regional focus mentioned in the title defines the purpose of the system, and the dataset design has been shaped in accordance with the technical requirements of object detection.

Datasets focusing on animal and plant species have been grouped into four main categories:

- **Goat Species Dataset:** This dataset, which includes Ankara goat, wild goat and other goat breeds, was created specifically for monitoring local fauna and species differentiation.
    - Images from different open data sources were used in the creation of the dataset, and the dataset created by us was also included in the study [30].
- **Arthropod and Insect Species Dataset**: This dataset contains species that are critical for user safety during nature walks. Some of the species included are the Mediterranean recluse spider, the Anatolian yellow scorpion, and the fruit fly. Various open data sources were used in the creation of the dataset, and the resulting images were labeled in a way suitable for model training [24-30].
- **Mushroom Species Dataset**: This dataset, which includes mushroom species found in the Muğla region, has been prepared for regional species identification and classification studies. While the focus of the dataset is the chanterelle mushroom, which is commonly found in the forests of Muğla, it has been diversified with different mushroom species. Open

access data sources were used in the creation of the dataset, and the dataset created by us was also included in the study [29,32].

- **Plant Species Dataset**: This dataset, which includes common plants specific to the Muğla region, was created for the purpose of flora identification and species differentiation. The dataset includes sage, bellflower and thyme species. In the creation of the dataset, images obtained from open data sources and the dataset created by us were used together [31,32].

The datasets were created using various open datasets available on the commercial and academic platforms Rob flow and Kaggle. Data augmentation techniques were applied using the Augmentations library to reduce class imbalances in the dataset and improve the generalization ability of the model. The augmentation techniques applied included transformations such as brightness and contrast changes, horizontal flipping, and random clipping.

The generated dataset was divided into 80% training, 10% validation, and 10% testing data. This allowed for a balanced evaluation of both the learning process and overall performance of the model. Tables 2-5 show a balanced distribution of the datasets.

Table 2: Distribution of Goat Species Data Set.

Class	Number of Images
Angora Goat	1023
Aleppo Goat	765
Honamlı Goat	814
Kilis Goat	940
Angora Goat	1275
Maltese Goat	810
Norduz Goat	702
Saanen Goat	887
Wild Goat	3301
Total	**10.517**

Table 3: Distribution of Arthropod and Insect Species Data Set.

Class	Number of Images
Red Spider	2.481
Mediterranean Hermit Spider	3.432
Anatolian Yellow Scorpion	4.602
Corn Roundworm	2.029
Killer Bee	2.049
Brown Stink Bug	2.396
Fruit fly	1.879
Aphids	2.394
Egyptian Worm	2010
Potato Beetle	1.995
Autumn Army Wolf	2,000
Black Scorpion	2.796
Total	**30,063**

Table 4: Distribution of Mushroom Species Data Set.

Class	Number of Images
Chanterelle Mushroom	1449
Bread Mushroom	1006
Emperor Mushroom	139
Snowfall Mushroom	118
Cultivated Mushrooms	315
Fly agaric	299
Total	**3326**

Table 5: Distribution of Plant Species Data Set.

Class	Number of Images
Sage Plant	40
Bellflower	39
Foxglove	39
St. John's Wort	38
Oleander Flower	35
Cistus Flower	36
Fern	19
Thyme Plant	40
Carob	29
Total	**315**

The relatively limited size of the plant species dataset (315 images) stems from the difficulty of photographing species in their natural environment and the inadequacy of existing open data sources. However, the generalization ability of the model was supported by applying data augmentation techniques, and the resulting value of 0.908 mAP@0.5 demonstrates how effective the YOLOv11n architecture combined with transfer learning can be on small datasets. Indeed, high accuracy has been reported in the literature with datasets of similar sizes [4,5]. It is acknowledged that the performance of the model should be interpreted more cautiously for species with a low number of images per class (e.g., Fern: 19 images), and expanding the dataset is among the priority goals for future studies.

Materials Used

The materials used in this study play a critical role in both model training and mobile application development processes:

Object Detection Architecture: YOLOv11n

YOLOv11 (You Only Look Once, version 11), is one of the latest convolutional neural network architectures developed for object detection [22]. In this study, the YOLOv11n (nano) variant was preferred. The reasons for its selection and the characteristics of the model are as follows:

- **Superior Speed and Efficiency**: YOLOv11 has faster inference capabilities and is more efficient in terms of model size (number of parameters) compared to its previous versions. The Nano variant is particularly suitable for resource-constrained mobile devices and edge computing. It is optimized for computing environments. This enables the real-time requirements of the mobile alert system to be met.
- **Training Process and Model Weights**: The model was trained separately for each dataset, and the best-performing model weights were saved as best.pt files. Advanced Backbone Architecture: The model provides more efficient feature extraction thanks to its Spent (Cross Stage Partial Network) based structure.
- **Multi- Scale Feature Fusion**: PANet (Path) for efficiently combining features at different scales. Aggregation Network was used.
- **Anchor-Free Detection**: Traditional anchor It offers a simpler and more effective detection mechanism than the box

approach.

- **Self- Attention Mechanisms**: Enhanced attention mechanisms provide high performance, especially in detecting small objects.
- **Real-Time Detection**: The model can analyze images in seconds and perform instant species identification.
- **High Accuracy**: Provides accurate detection even in complex natural environmental conditions, including shadows or background interference.
- **Low Latency and Optimization**: It has a lightweight and optimized structure that can run on mobile devices.

The YOLOv11n model has been trained to perform exceptionally well on photographs of animal and plant species taken from various sizes and angles, offering an ideal object detection solution for mobile applications.

LLM (Large Language Models)

In this study, Large Language Models (LLMs) were used to generate scientific and informative texts about the identified animal species. The LLM-based system takes the object tag identified by the YOLOv11n model and generates descriptive content appropriate to that tag. As a model, meta- llama /Llama-4-Scout-17B-16E-Instruct was selected [23]. This model provides high accuracy and contextual consistency with 17 billion effective parameters and 16 expert structures. LLM produces detailed and understandable information about the characteristics, habitat, behavior, agricultural impacts and interactions with humans of the identified species. The generated content is presented to the user in Turkish.

For performance measurement, the generated texts were prepared using pre-prepared groundwork. These texts are compared with truth texts. These texts, prepared for a total of 31 different animal species, were created using articles, magazines, and news sources from the internet. Each species includes detailed information on characteristic features, habitat, behaviors, and agricultural impacts, and ground truth is used as a reference to evaluate the accuracy and contextual consistency of LLM outputs (C. Div, 2026) [30]. Some example texts are given in Table 6.

Table 6: Ground Truth Data.

Category	Text
Angora Goat	Ankara goat (Capra) haircuts The Angora goat (Anatolian acyesis) is a domestic goat breed native to the Ankara region of Turkey. ** Characteristics: ** It is a medium-sized, robust goat. **Habitat: ** It is adapted to the continental climate of Anatolia. ** Behavior: ** It lives in herds and is herbivorous. ** Impacts on Agriculture: ** It is raised for the production of mohair, used in the luxury textile industry. It is shorn twice a year. Its mohair is lightweight, elastic, and flame-retardant. Meat yield is low, and it is primarily valued for mohair production. It contributes to the local economy.
Mediterranean Hermit Spider	Mediterranean Hermit Spider (Loxosceles) The spider (Acacia rufescens) is a species of spider native to the Mediterranean basin. ** Characteristics: ** * Body length is approximately 7-10 mm. **Habitat: ** * Lives in secluded corners of houses and basements. ** Behavior: ** * Lives secretly. ** Impacts on Agriculture: ** * It has no direct impact on agriculture. Its bite can cause necrotic wounds. It is a species that requires caution regarding human health.
Killer Ari	Killer bee (Apis) mellifera the scutellata hybrid is an aggressive honey bee hybrid. ** Characteristics: ** It is an African honey bee hybrid. **Habitat :** It can adapt to various climatic conditions. ** Behavior: ** It is extremely defensive and aggressive. ** Impacts on Agriculture: ** It contributes to agriculture through pollination. However, its aggressive nature poses a risk to agricultural workers. Although honey yields are high, it is difficult to control.

Rice Gall Fly	Rice Gall Fly (Roselia) The gnat (Asterisks oryzae) is a species of fly that is a pest of rice. ** Characteristics: ** * Its larvae form galls in the rice stalk. **Habitat: ** * Found in rice fields. ** Behavior: ** * Feeds inside the stalk. **Effects on Agriculture: ** * Causes 'silk gall ' formation in the rice stalk. Prevents water and nutrient transport in the plant. Leads to reduced tillering and yield loss. It is a significant pest in rice-producing regions.
Humanly Goat	The Humanly goat is a breed native to the Taurus Mountains region of Turkey. ** Characteristics: ** It has a large build and strong legs. **Habitat :** It lives in rugged terrain. ** Behavior: ** It has high mobility. **Impacts on Agriculture: ** It is raised for combined yield (meat and milk). It efficiently converts roughage into meat and milk. Its breeding is encouraged to preserve genetic diversity.

Ground In the creation of truth texts, a multi-source verification approach has been adopted to ensure the accuracy and reliability of the information. For each type, content has been compiled from multiple independent sources, including peer-reviewed scientific articles and academic databases, publications of official national institutions such as the Ministry of Agriculture and Forestry and TÜBİTAK, and academically cited articles from multi-source encyclopedic platforms such as Wikipedia, and prepared using a cross-verification method. Information in a source cannot be published without being confirmed by at least one independent secondary source. This information was not included in the truth text. During this process, support from an expert biologist was not sought, which is considered one of the main limitations of the study. Future studies plan to create a reference dataset enriched with field expert oversight.

- **BLEU**: Measures the word-level agreement between the generated text and the reference text.
- **ROUGE**: Evaluates the overlap between word and phrase level outputs and reference texts.
- **METEOR**: Measures semantic similarity by considering the semantic and morphological structure of a language.
- **BERT Score**: Evaluates content in terms of both word similarity and semantic accuracy, preserving contextual integrity.

These metrics allow for a comprehensive assessment of the accuracy, fluency, and contextual consistency of the texts generated by the model. Furthermore, the use of the Grow API enables the model to run quickly and with low latency, providing mobile application users with real time and reliable information.

Mobile Application Interface

The Animist mobile application developed in this study is to enable users to identify species through photographs, record the locations of identified species, and systematically view past scan records. The application works integrated with an artificial intelligence-based image processing API and performs bidirectional data transfer between the mobile device and the server. The Flutter library was used in the development of the mobile application. Dart was used for application coding, and Firebase was used for the database. Hugging was used for the animal and plant recognition API. The Facebook platform was used.

As a result of the entire process, the database, storage, location services, machine learning based API integration, camera operations, and authorization system have been integrated and made to work seamlessly within a single application. Animist now has an integrated structure that allows users to perform live photo recognition while simultaneously accessing browsing history, location information, and administrative controls.

Our System Model

end-to- end architecture that combines YOLOv11-based object detection and Large Language Model (LLM)-based annotation generation processes. The system offers a mobile user interface, a robust backend, and AI integration. The overall operation encompasses the processes of visualization, annotation generation, and storage of images submitted by the user. Figure 1 shows a general diagram of the ANIPICT system and visualizes the data flow, model integration, and mobile user interaction.

The system begins with the data collection phase. Images of animal and plant species are compiled from various sources, both from publicly available datasets and through manual downloads. The collected images undergo preprocessing; cleaning, labeling, and data augmentation techniques using the Augmentations library are applied to ensure class balance.

The YOLOv11n model was trained on the prepared datasets, which were divided into 80% training, 10% testing, and 10% validation. the hyperparameters used in model training. A higher epoch value was used for the goat dataset to allow for longer model training, while a lower epoch and batch size were preferred for the insect dataset. All models were trained in the Kaggle GPU environment. Table 7

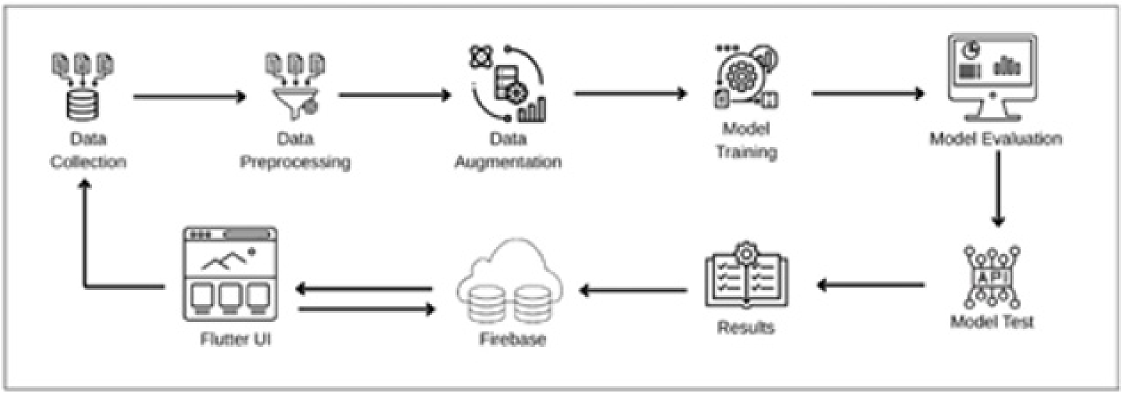

Figure 1: General Architecture.

Table 7: Model Training Parameters.

Model	Epoch	Batch You	Image Size	Optimize r	Learning Rate	Hardware
YOLOv11n (Goat)	400	16	640	AdamW	lr 0=0.005, lrf =0.001	Kaggle GPU
YOLOv11n (Insect)	100	8	640	Default	lr 0=0.005, lrf =0.2	Kaggle GPU
YOLOv11n (Plant)	100	16	640	Default	lr 0=0.01 lrf = 0.01	Kaggle GPU
YOLOv11n(Mushroom)	200	16	640	Default	lr 0=0.01 lrf = 0.01	Kaggle GPU

In the plant dataset training, 100 epochs and 16 batch sizes were preferred, while the learning rates were kept constant at the default values. For the mushroom dataset, however, the number of epochs was increased to 200, making the training process more comprehensive. In both models, the image size was set to 640 pixels, and YOLO's standard settings were used during the optimization process to aim for stable convergence.

The model's performance was evaluated using mAP@0.5 and loss values, and the best weights were determined. After training is complete, the model starts serving the mobile application via Fast API, and images uploaded by the user are processed through the API, with the results stored in a Firebase database.

The animal and plant identification diagram is supported by LLM integration, specifically designed to provide users with real-time notifications of endangered species and detailed information. The animal image uploaded by the user is routed to the relevant YOLOv11n model running on Fast API. The identified species name is transmitted with high reliability to the Llama-4-Scout 17B model via the Grow API. The LLM generates Turkish descriptions including the species' biological characteristics, agricultural impacts, and risks in human interaction. The results and metric visualizations are stored in Firebase and presented to the user in real-time via the mobile application.

Overall, the ANIPICT model is an end-to-end system that combines the detection and description processes of both animal and plant species, providing mobile users with real-time and detailed information. Figure 1 clearly visualizes the system's overall architecture, data flow, and user interaction; Figure 2 shows the animal and plant recognition workflow.

Findings

The performance of the ANIPICT system was evaluated under three main headings: technical metrics of object detection models, semantic accuracy of content generated by the Large Language Model (LLM), and end-to-end functionality of the system.

Model Performance Results

The YOLO-based models trained within the system were tested on four different datasets (Animals 1-2 and Plants 1-2). The classification and positioning performance of the models is summarized in Table 8.

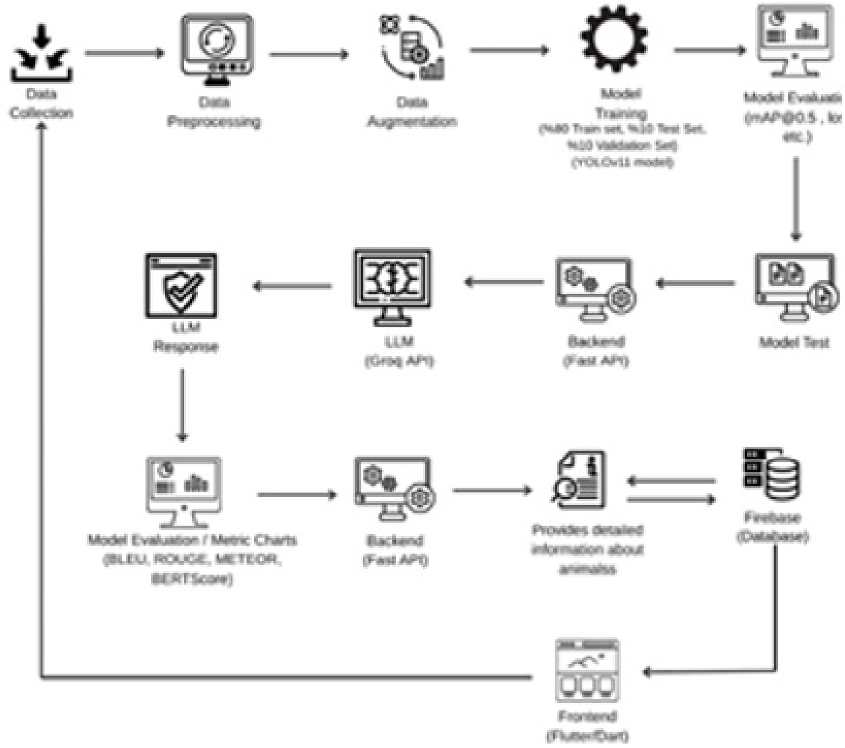

Figure 2: Animal and plant identification diagram.

Table 8: Model Performance Results According to Data Sets.

Data Set	Precision	Recall	F1-score	mAP@0.5	mAP@0.5:0.95
Animals 1. Dataset [30]	0.792	0.742	0.767	0.801	0.533
Animals 2. Dataset [30]	0.865	0.887	0.877	0.889	0.709
Plants 1. Data Set [31]	0.913	0.925	0.919	0.964	0.735
Plants 2. Dataset [29]	0.841	0.856	0.848	0.908	0.649

The findings show that the Plants 1 (Fungus) dataset has the highest performance with a map value of 0.964. This proves that the distinctive morphological features of fungal species were learned with high accuracy by the model. In the animal datasets, arthropods (Animals 2) were observed to perform better than mammals (Animals 1).

Big Language Model (LLM) Assessment Results

ANIPICT not only performs species detection but also generates contextual information about the detected species using the Meta-LLaMA-4-Scout-17B model via the Grow API. The accuracy of the generated texts was analyzed using NLP metrics. In this study, the LLM output quality was examined qualitatively and quantitatively through a representative sample. A comprehensive statistical analysis of the overall LLM performance of the system was conducted using existing ground Since expanding the truth dataset and establishing a multi-query evaluation infrastructure were necessary, this study presents an example evaluation using the Black Scorpion species, which was selected as a representative sample from the dataset. This approach serves as a proof -of-concept assessment to demonstrate the language production quality and contextual consistency of the model. The metric results are given in Figure 3.

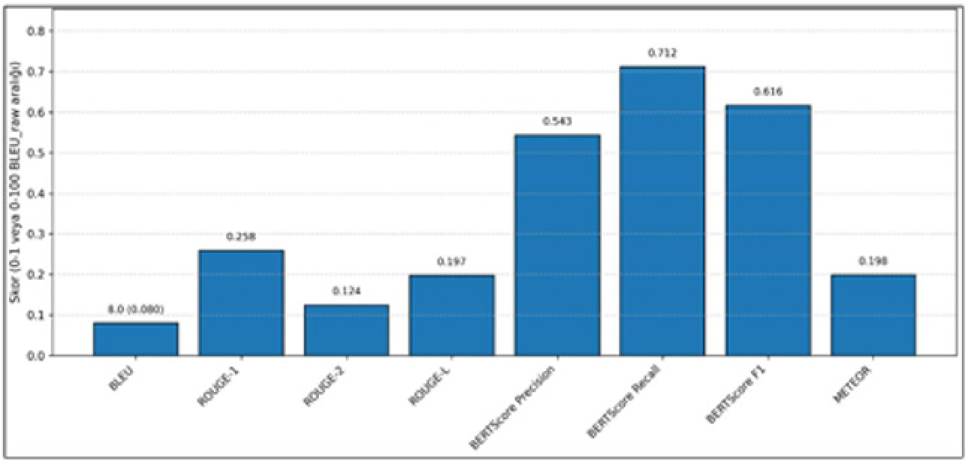

Figure 3: Comparison of LLM Output Metrics on the Black Scorpion Dataset.

Semantic Achievement: BERT Score The high Recall (0.712) and BERT Score F1 (0.616) values indicate that the information produced by the model exhibits a strong semantic agreement with scientific facts. In other words, the model was able to correctly capture the main meaning and context in the reference texts, and the content presented to the user was reliable. Syntactic Flexibility: The relatively low BLEU (0.080) and ROUGE-L (0.197) scores indicate that the model does not follow the reference texts word for word, but instead rephrases the information in an original, fluent, and descriptive language. This does not impair the semantic accuracy of the texts; it simply results in low syntactic or word-level similarity.

Overall Assessment: Considering the METEOR (0.198) score, it is seen that the model does not merely present memorized patterns, but produces contextually appropriate content with depth of meaning. Low syntactic scores confirm that the model produces original texts without loss of meaning thanks to its flexible and creative use of language. These results were obtained from a specific prompt (Black Scorpion example); metric values may vary depending on the species being queried and the details of the prompt used.

System Integration and User Experience

Flutter and Firebase infrastructure, has achieved the following functional successes in field tests:

- **Hybrid Recognition Logic**: The system's hierarchical decision-making mechanism, which automatically activates plant/fungus models when it cannot find animals in an image, is working successfully.
- **Geographic Data Continuity**: Thanks to Google Maps integration, locations where species were identified (with neighborhood/street details) and reliability scores are archived in real time on Fire store.

Administrative Control: Thanks to the developed Super Admin panel, content (CRUD operations) and user roles (User, Content Admin, Super Admin) can be managed. The scalability of the system has been proven by providing dynamic management (Admin). Sample interfaces of the developed system are as follows; Figure 4 shows the mobile application's home screen. Figure 5 shows the screen displaying the insect species recognition results performed by the artificial intelligence model, and Figure 6 shows the plant, insect, and animal recognition history screen.

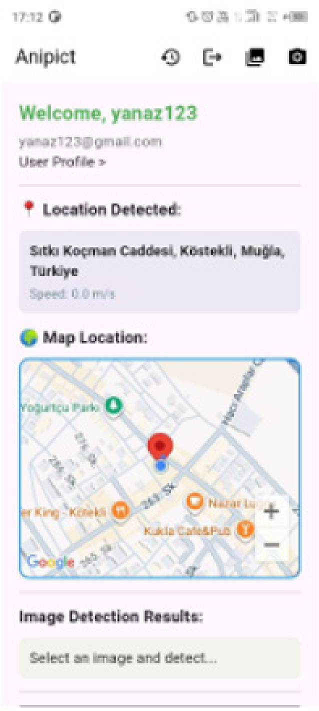

Figure 4. Mobile Application Home Screen

Figure 5. Insect species recognition result.

Figure 6. Screen of previous plant, insect, and animal identification history.

Conclusion And Recommendations

This study develops an AI-powered mobile system called ANIPICT, which aims to automatically detect commonly found insect, animal, and plant species in forested areas of the Muğla region from images and provide the user with real-time, descriptive information. The system is designed with an end-to-end architecture consisting of a YOLOv11n-based object detection model, a Large Language Model (LLM), a Fast API- based backend, and a Flutter- based mobile application. Experiments conducted on datasets of different living groups have shown that the models achieve high mAP@0.5 values and can operate effectively in a mobile environment with low computational cost.

Thanks to the support of object detection results with LLM, the user is provided not only with the species name but also with descriptive information about biological characteristics, agricultural impacts, and potential risks. The generated texts were evaluated with BLEU, ROUGE, METEOR, and BERT Score metrics, and reliable results were obtained in terms of semantic consistency. In this respect, the system has gone beyond being just a recognition tool and transformed into an information-driven decision support structure.

The mobile application's scalable and platform-independent structure is supported by features such as location-based data storage and map integration, thus providing a suitable infrastructure for both individual use and long-term environmental data collection studies.

This study has some limitations. The LLM evaluation was performed on a single species to representatively demonstrate the system's language generation capability. A statistical LLM evaluation encompassing the entire species catalog was excluded from this study and is planned for future research. Future research is recommended to expand the datasets, optimize real-time and offline usage scenarios, enhance LLM outputs with expert resources, and integrate the system with official institutions. In addition, the ground used in the LLM assessment Reviewing the truth dataset by experts in the fields of biology and agriculture will significantly enhance the scientific credibility of the system. Accordingly, it is considered that ANIPICT can serve as a foundation for broader-scale applications in the areas of nature security, agriculture, and environmental awareness.

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