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AI-Based Monitoring of Swiftlet Nests: ClassifyingShapes for Enhancing Farming Practices

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Abstract:

Swiftlet farming, a cornerstone of the edible bird nest industry, holds significant economic importance, particularly in Southeast Asia. The nests, crafted from the saliva of swiftlets, are highly valued for their nutritional and medicinal properties. Traditional methods of monitoring swiftlet nests are labor-intensive, prone to human error, and lack the precision needed for optimizing yield and quality. Despite advances in farming techniques, challenges such as inconsistent nest shapes, improper environmental conditions, and the inability to detect anomalies early have limited the industry's potential.AI-based monitoring systems offer a transformative approach to addressing these issues. By integrating machine learning and image processing techniques, the systems classify nest shapes, track growth stages, and identify abnormalities that indicate environmental or health concerns. The study introduces an AI-driven framework for swiftlet nest monitoring, aiming to overcome the limitations of traditional practices. Using high-resolution imaging and convolutional neural networks (CNNs), the system categorizes nest shapes and provides actionable insights for farmers. This innovation modernizes an age-old practice, bridging the gap between traditional farming methods and cutting-edge technology. The system ensures ethical and sustainable practices, leading to enhanced product quality, increased profitability, and better ecological balance in swiftlet farming. The significance of the research lies in its potential to modernize an age-old practice, bridging the gap between traditional farming methods and cutting-edge technology. By ensuring ethical and sustainable practices, the adoption of AI can lead to enhanced product quality, increased profitability, and better ecological balance in swiftlet farming.

Keywords: Keywords: Swiftlet Farming,AI-based Monitoring Systems, Machine Learning, Image Processing, Convolutional Neural Networks (CNNs), Nest Shape Classification, Nest Growth Stages, Abnormalities Detection, Environmental Monitoring, Sustainable Farming Practices, Agricultural Innovation, AI-driven Framework, Profitability in Swiftlet Farming.

1. INTRODUCTION

Swiftlet farming is a lucrative industry, particularly in Southeast Asia, where the nests of swiftlets are harvested for edible bird nests (EBN). The quality and shape of these nests are directly linked to their value in the market. Traditional methods of monitoring and classifying nest shapes involve manual inspections, which are labor-intensive, time- consuming, and prone to human errors. Additionally, farmers often struggle to consistently track the growth stages and shapes of nests, making it challenging to predict the right time for harvesting.

The problem lies in the need for an efficient, automated system that can quickly and accurately classify swiftlet nest shapes based on images. As the demand for high-quality EBN grows, farmers require a reliable solution that reduces human involvement in the classification process, minimizes errors, and improves overall productivity. The task is complex due to the variations in nest shapes and the large amount of image data that needs to be processed regularly. Current solutions lack scalability, consistency, and the ability to handle a variety of nest shapes that may vary due to environmental conditions or swiftlet species.

Thus, the project addresses the problem of automating swiftlet nest shape classification by leveraging advanced image processing, machine learning, and deep learning algorithms. The objective is to develop an AI-based system capable of accurately classifying images of swiftlet nests into predefined categories (such as bowl-like, oval, and corner-like shapes), which will help farmers make informed decisions about nest harvesting, improve quality control, and streamline their operations.

2. LITERATURE SURVEY

Chua and Zukefli [1] comprehensive review investigate into the multifaceted world of edible bird's nests (EBN) and swiftlet farming. They explore the biochemical compositions of EBN, including factors such as color, nitrate, and nitrite contents, alongside the ongoing research into their potential medicinal applications. Hao and Rahman [2] provide a comprehensive overview of the swiftlet industry in Asia, focusing on the taxonomy of swiftlets, the lucrative nature of the EBN market, and the challenges faced by the industry. They discuss the taxonomic ambiguity surrounding swiftlets, highlighting the difficulties in classification despite efforts based on morphological, behavioral, and genetic traits. Syarafi et al. [3] examine the potential and sustainability of the swiftlet industry in Malaysia, focusing on factors affecting productivity, market value, and industry growth. They discuss the influence of environmental factors such as food resources, molt process, and reproduction on swiftlet nest production, emphasizing the interplay between productivity and environmental conditions. Hadi et al. [4] review focuses on the business factors influencing the Malaysian EBN swiftlet ranching industry. They identify ten key characteristics, including invention, knowledge, resources, and marketing programs, that impact the success of new businesses in the sector. Quah and Chong [5] review delves into the phenomenon of reptile predation on swiftlets, particularly focusing on commercially farmed species of the genus Aerodramus. They analyze literature and online records to identify various reptile species known to prey on swiftlets across different regions. Smith et al.[6] developed a convolutional neural network (CNN)-based system for bird nest detection. The study focused on detecting nests from aerial imagery using UAVs. They achieved high accuracy with a dataset containing diverse environments. However, the approach was limited to general nest detection without classification. Chen and Liu[7] investigated the use of random forest classifiers to optimize agricultural practices, including crop disease identification. Their work emphasized feature extraction from images and highlighted the importance of combining traditional and deep learning techniques. Martínez et al.,[8] implemented IoT-based monitoring systems for environmental factors affecting agriculture. Although focused on crop farming, the research provided a foundation for integrating IoT sensors in monitoring systems. Rahman et al., [9] explored the physical characteristics of swiftlet nests, identifying the need for classification systems in farming. The study manually classified nests into categories such as "mangkok" and "oval," emphasizing their economic significance. [10] Khan et al. utilized AlexNet for small datasets in agricultural applications. Their work demonstrated the

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potential of transfer learning to overcome dataset limitation. Brown et al.[11] implemented computer vision techniques for identifying species in wildlife images. Their approach was among the first to apply AI in ecological conservation. Huang and Tan [12] explored image processing techniques to analyze nest structures. Their approach relied on edge detection and geometric modeling. Ali et al. [13] studied sustainable practices in swiftlet farming, emphasizing the economic benefits of high-quality nests. The study pointed out inefficiencies in current monitoring methods, calling for technological intervention. Jones [14] implemented machine learning in livestock monitoring, focusing on health and productivity. While not directly related to bird farming, the techniques are relevant to swiftlet monitoring systems.

3. PROPOSED METHODOLOGY

The project focuses on leveraging artificial intelligence (AI) to automate the monitoring and classification of swiftlet nests, addressing the challenges of traditional methods. Swiftlet nests, made primarily of edible bird saliva, are highly valued in the global market, especially in the food and health industries. The classification of nest shapes (e.g., bowl-shaped, oval, or corner-shaped) is essential for determining quality and market value. The traditional manual methods for monitoring nests are labor-intensive, error-prone, and inconsistent, creating a demand for a more efficient and accurate solution.

Key Components of the Project:

Dataset Preparation:

The project involves a data-set containing images of swiftlet nests categorized into three shapes: **bowl-shaped (mangkok)**, **oval**, and **corner-shaped (sudut)**.

Preprocessing steps like re-sizing and normalizing images are applied to ensure compatibility with AI models.

Feature Extraction:

Advanced AI techniques, including **AlexNet**, are used to extract meaningful features from images. These features represent the unique characteristics of different nest shapes.

Model Training:

Machine learning models, including **Random Forest Classifier** and **Decision Tree Classifier**, are trained on extracted features to classify nest shapes accurately.

The project saves these models for future predictions, ensuring scalability and reusability.

Evaluation Metrics:

Metrics like accuracy, precision, recall, and F1-score are used to evaluate the performance of the models, ensuring reliability in classification.

Automation:

The developed AI system automates nest shape classification, reducing human intervention and enabling faster decision-making.

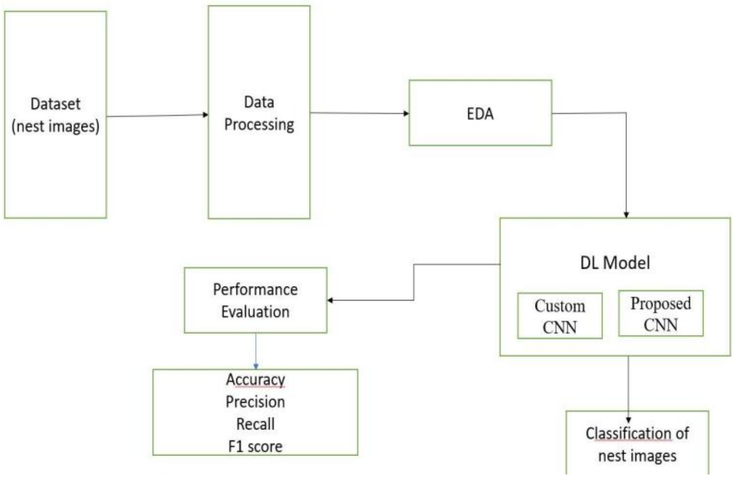

Fig 1 Proposed Block Diagram of nest image classification

Workflow

Data Collection and Dataset Preparation:

Collect images of swiftlet nests categorized into classes: **Mangkok (Bowl-shaped)**, **Oval**, and **Sudut (Corner-shaped)**.

Ensure high-quality images with diverse lighting and environmental conditions to improve model robustness.

Feature Extraction:

Two approaches are used for extracting features:

Traditional Feature-Based Approach: Reshaping image arrays to vectors and using them as input for models like Decision Trees and Random Forest.

Deep Learning-Based Approach:

Use **AlexNet**, a pre-trained Convolutional Neural Network (CNN), to extract deep features from images.

AlexNet processes images through multiple convolutional layers, pooling layers, and ReLU activations to extract meaningful features.

Model Building:

Traditional Machine Learning Models:

Train models like **Decision Tree** and **Random Forest** using the extracted features.

Evaluate performance on the testing set to identify the best model.

Deep Learning Approach:

Extract deep features using **AlexNet**'s feature layer.

Train **Random Forest** on the extracted features for classification.

Training and Testing:

- Split the dataset into **training** (80%) and **testing** (20%) sets.
- Train the models on the training set using extracted features.
- Test the trained models on the testing set to evaluate metrics such as:

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- Accuracy

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- Precision
- Recall
- F1 Score

Step-by-Step CNN Model Building Process

1. Data Preprocessing

- Collect and preprocess images of swiftlet nests.
- Resize all images to a fixed shape (e.g., 128×128×3).
- Normalize pixel values to the range [0,1] by dividing by 255.
- Apply data augmentation (rotation, flipping, brightness adjustment) to increase dataset diversity.
- Convert labels (nest categories) into one-hot encoding for multi-class classification.

2. Model Compilation

- Optimizer: Adam (adaptive learning rate optimization)
- Loss Function: Categorical Crossentropy (since it's a multi-class classification problem)
- Metrics: Accuracy, Precision, Recall, F1-score

3. Model Training

- Train using batch size = 32, epochs = 50-100 (based on early stopping criteria).
- Implement early stopping and learning rate reduction to optimize performance.
- Monitor training and validation loss/accuracy to prevent over-fitting.

. Model Evaluation & Deployment

- Test on unseen images to validate model performance.
- Save model as a .h5 file for deployment.
- Deploy in an IoT-based monitoring system for real-time nest classification

4. EXPERIMENTAL ANALYSIS

Figure 1 shows the dataset consists of 900 images of swiftlet nests categorized into three classes: Mangkok, Sudut, and Oval, with 300 images per class. Each image represents a different nest shape, commonly found in swiftlet farming. The images are captured under varying conditions to improve model robustness. The dataset is designed for AI-based classification to assist farmers in identifying and managing nest types efficiently. All images are in RGB format and require preprocessing (resizing, normalization, augmentation) before model training. This dataset aims to enhance automated monitoring and management in swiftlet farming using deep learning.

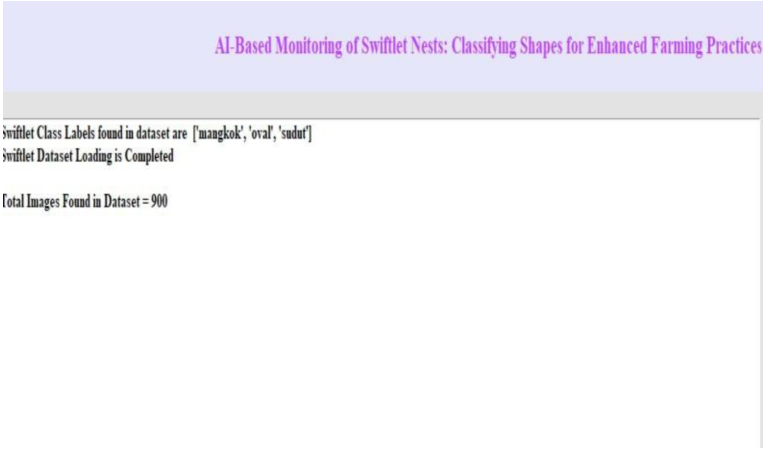

Fig 1 Uploading dataset

The count plot will show an increased number of images for each class, depending on how many augmented images were generated. If augmentation was applied equally to all classes, the bars will still be of equal height. The count plot helps visualize data distribution after augmentation, ensuring that the dataset remains balanced for better model performance.

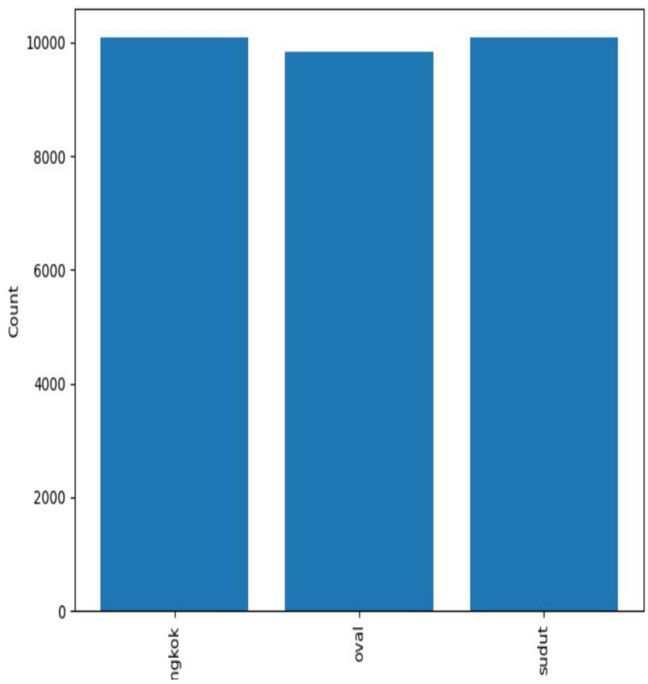

Fig 2 : Count Plot of nest images

The confusion matrix for custom CNN model shows how well the model classifies the swiftlet nest categories "mangkok," "oval," and "sudut." It highlights the number of correctly classified instances (true positives) versus misclassifications (false positives and negatives), indicating its overall precision and recall

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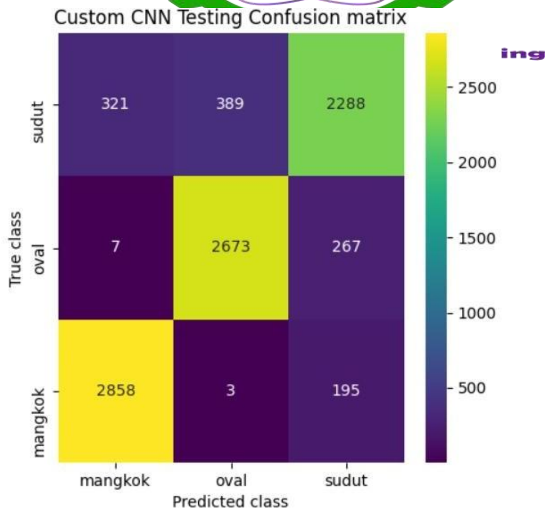

Fig 3 Confusion Matrix of custom CNN model

CNN likely stands for Convolutional neural network, a deep learning model. As shown in Figure 4, it includes metrics such as precision, recall, and F1-score, for both classes (benign and attack) based on the CNN model's predictions. These metrics help to evaluate how well the model is performing in terms of classifying instances correctly and understanding its strengths and weaknesses.

Custom CNN Testing Accuracy : 86.868125763804
Custom CNN Testing Precision : 86.7051332177515
Custom CNN Testing Recall : 86.8469655560407
Custom CNN Testing FScore : 86.7018895455641

Fig 4 Accuracy obtained by using custom CNN model

The confusion matrix for the Proposed CNN demonstrates its superior ability to handle complex decision boundaries by showing higher true positive counts for each category. It often exhibits fewer misclassifications than the custom CNN due to its ensemble approach, improving classification accuracy.

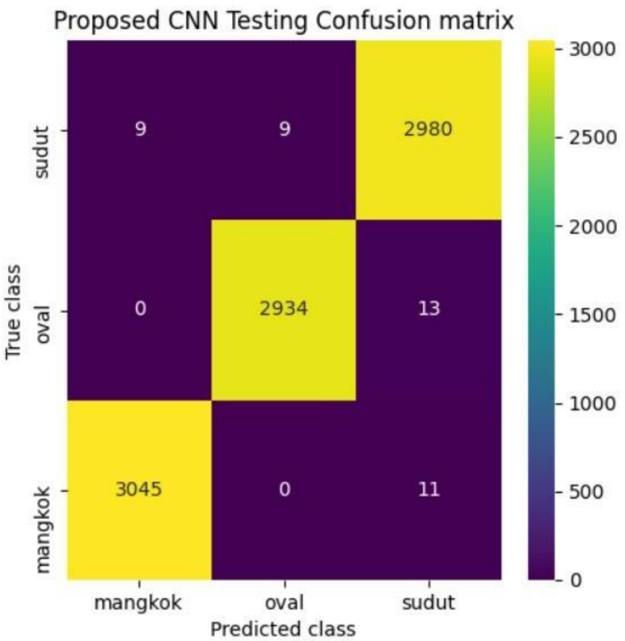

Fig 5 Illustration of confusion matrix obtained using Proposed CNN model

Proposed CNN Testing Accuracy : 99.5333851794245
Proposed CNN Testing Precision : 99.5335197891495 8
Proposed CNN Testing Recall : 99.53284183992793
Proposed CNN Testing FScore : 99.53312886070542

Fig 6 Accuracy obtained using Proposed CNN model

Table 1 presents a performance comparison between two classification models the custom CNN model and Proposed CNN model. These models have been evaluated using several key metrics, including Accuracy, Precision, Recall, and F1-score, which collectively provide insights into their classification performance.

Table 1. Performance comparison of custom CNN and proposed CNN model

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Custom CNN model	86.8	86.7	86.8	86.7
Proposed CNN model	99.5	99.5	99.5	99.5

Finally, Table 1 clearly illustrates that Proposed CNN model outshines the custom CNN model in terms of all the evaluated metrics. The Proposed CNN model boasts exceptional accuracy and exhibits remarkable Precision, Recall, and F1-score values, reflecting its superior performance.

Fig 7 Predicted output nest image as Oval

5. CONCLUSION

The systematic review of three themes in swiftlet farming reveals significant advancements and challenges in integrating digital technologies, AI analysis, and innovative solutions to enhance efficiency and sustainability. The first theme highlights the pivotal role of smart monitoring and control systems, showcasing technologies like WSN and IoT in optimizing swiftlet habitats for improved productivity. However, challenges persist in accessibility and compatibility, necessitating further research and adaptation for widespread adoption. The second theme underscores the potential of AI-driven bird detection techniques, although limitations in accuracy and processing speed require attention for real-time applications. Similarly, innovative approaches in EBN production and quality grading demonstrate promising advancements but face hurdles in scalability and practical implementation. Addressing challenges related to infrastructure, economic constraints, and ecological harmony is crucial for ensuring the successful integration of digital technologies in swiftlet farming. Furthermore, bridging the digital divide and fostering collaborative efforts among stakeholders are essential for extending the benefits of digitalization to all farmers. Overall, while the findings signify significant progress in revolutionizing swiftlet farming practices, further research and concerted actions are imperative to overcome existing obstacles and realize the full potential of digital technologies in enhancing agricultural sustainability and productivity, ultimately benefiting both the research field and the broader community.

The future scope of the AI-based swiftlet nest monitoring system is vast, with potential applications in smart farming and precision agriculture. By integrating IoT sensors and real-time monitoring, the system can automate the identification and classification of swiftlet nests, reducing manual labor and improving efficiency. Advanced deep learning models with real-time image processing can enhance accuracy, helping farmers make data-driven decisions. The system can be expanded to detect nest quality, monitor environmental factors, and predict swiftlet behavior for better farming outcomes. Integration with mobile applications can provide farmers with instant alerts and recommendations. Further, the use of cloud-based AI can enable large-scale data collection and improve the model through continuous learning. Future enhancements could involve edge computing, allowing real-time processing on low-power devices. AI-powered swiftlet population monitoring could help in biodiversity conservation and sustainable farming. Additionally, the technology could be adapted for other bird species and nest classification in wildlife conservation. With advancements in AI and automation, this project has the potential to revolutionize swiftlet farming and ecological monitoring globally

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