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Artificial Intelligence-Powered Cyclone Classification Framework Using Mobilenetv1 and Goose Optimizer: Climate-Resilient Farming

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Abstract

The intensifying frequency of cyclones owing to climate change presents a substantial threat to agricultural productivity, particularly in coastal and climate-sensitive regions. The present work proposes an artificial intelligence (AI)-powered framework for climate-resilient farming. The proposed AI framework consists of a pre-trained convolutional neural network (CNN), specifically the MobileNetV1 architecture. This architecture enables efficient feature extraction, making it well suited for real-time applications in resource-constrained agricultural systems. MobileNetV1 was fine-tuned using hyper-parameters, such as the number of epochs, learning rate, and batch size. A dataset of 1,600 satellite images was created with four distinct cyclone classes: tropical depression (class 1), tropical storm (class 2), severe tropical storm (class 3), and typhoon (class 4). The model's performance was evaluated for various optimizers, and the goose optimizer emerged as the most effective. By leveraging adaptive gradient adjustments, the goose optimizer enhances the training process, achieving a classification accuracy of 98.33% and an area under the curve (AUC) of 100%. These results were further validated using a confusion matrix and receiver operating characteristic (ROC) curves. In addition, the superior performance of the proposed AI-powered framework was compared with other pre-trained CNN models, such as VGG16, VGG19, and ResNet, for different optimizers. The proposed AI framework offers a promising solution for empowering farmers with predictive intelligence, thereby enhancing their resilience in cyclone-affected agricultural systems.

1. Introduction

Cyclones affect agricultural systems, especially in coastal and low-lying regions, and are becoming more unpredictable and destructive according to the IPCC AR6 [1]. Hence, the classification of cyclones has become an important research area, and AI, particularly CNNs, has become a promising solution. Studies in [2, 3] have demonstrated the capability of CNNs to predict spatiotemporal weather anomalies with high accuracy. Authors in [4] demonstrated the potential of AI for severe weather events by integrating radar data and satellite observations. The developed model in [5] highlighted that while early warning systems exist, their disconnection from localized agronomic needs limits their efficacy. Table 1 shows four distinct classes of tropical cyclones based on sustained wind speed [6].

Table 1 Various classes in Tropical Cyclone

Class	Sustained winds
Tropical depression (Class 1)	≤33 knots ≤61 km/h
Tropical storm (Class 2)	34 - 47 knots 62 -88 km/h
Severe tropical storm (Class 3)	48 - 63 knots 89 - 117 km/h
Typhoon (Class 4)	64 - 84 knots 118 - 156 km/h

Class 1, referred to as tropical depression, includes cyclones with sustained winds of ≤33 knots (≤61 km/h). Class 2, designated as tropical storms, involves winds between 34 and 47 knots (62-88 km/h). Class 3, known as severe tropical storms, comprises cyclones with winds between 48 and 63 knots (89-117 km/h). Finally, Class 4, categorized as typhoons, features the most intense cyclones, with wind speeds between 64 and 84 knots (118-156 km/h). We developed AI-powered framework that classifies cyclones into four classes, as listed in Table 1. The rest of the paper is structured as follows. Section 2 presents related work, and Section 3 outlines the methodology. The proposed AI framework is detailed in Section 4, and the results are discussed in Section 5. Finally, the paper is concluded, and future work is presented.

2. Literature Review

Recent advancements in AI have significantly enhanced the accuracy of tropical cyclone classifications using satellite imagery. Authours in [7] introduced a two-stage deep-learning architecture that classifies tropical cyclone intensity using infrared satellite images. A similar multistage detection system combining Mask R-CNN and CNN classifiers was proposed in [8] using satellite images to classify tropical cyclones. Authors in [9] further expanded cyclone lifecycle identification by employing fluid noise augmentation and transformer-CNN hybrids to classify cyclone life stages from satellite sequences. Authors in [10] demonstrated the efficacy of MobileNetV2 for classifying environmental satellite imagery with high accuracy, outperforming VGG16. Authors in [11] integrated data augmentation and classical flow-based methods into a CNN pipeline for cyclone detection from satellite imagery, achieving an accuracy of above 90%. Authors in [12] also contributed to cyclone classification using CNNs on SAR-based satellite images, achieving an accuracy of 90.93%. The present work builds upon these contributions by using MobileNetV1 and Goose optimizer, with a classification accuracy of 98.33%.

3. Methodology

The methodology for the proposed AI-powered framework includes data collection, the development of the CNN model, and evolution.

3.1. Data Collection

A dataset of 1600 satellite cyclone images was compiled from publicly available websites. These images represent the various cyclone intensities. Each image was resized and normalized to ensure a uniform input to the CNN model. The dataset was split into training (70%), validation (15%), and testing (15%) subsets to ensure generalizability (Table 2).

Table 2 Dataset Details

Class	Number of Images			
	Training	Validation	Testing	Total
Class 1	280	60	60	400
Class 2	280	60	60	400
Class 3	280	60	60	400
Class4	280	60	60	400
Total	**1120**	**240**	**240**	**1600**

3.2. Model Architecture and Development

The CNN is based on the pre-trained MobileNetV1 architecture and fine-tunes the model for cyclone-specific features with hyper-parameters: epochs, learning rate, and batch size. The model was tested with multiple optimizers, including Adam, sea-horse, SGD, and goose. Moreover, the outstanding performance of the model was compared with other pre-trained CNN models, such as VGG16, VGG19, and ResNet.

3.3. Performance Evaluation

The model performance was evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC. These metrics were visualized using a confusion matrix and ROC curves.

4. Proposed AI Framework

The proposed framework is illustrated in Fig. 1. The dataset comprises satellite images, which undergo a pre-processing stage to normalize and prepare the data for training, validation, and testing. These pre-processed images were then input into MobileNetV1.

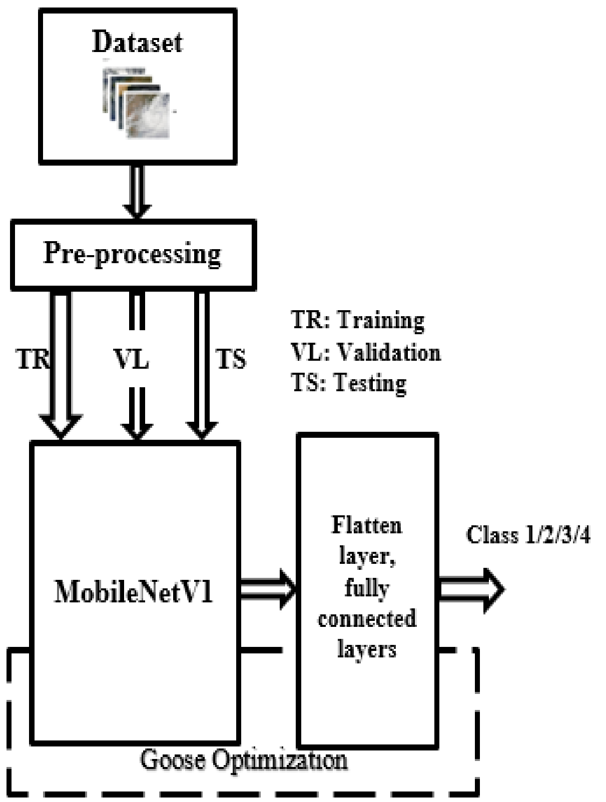

Figure 1 **Proposed AI framework**

MobileNetV1 is beneficial in tropical cyclone classification tasks owing to its lightweight architecture for extracting discriminative features from satellite imagery [10]. This model was trained on a dataset of 1600 satellite images and pre-processed for uniformity. In addition, the goose optimizer adapts learning rates dynamically using mechanisms similar to momentum or adaptive moment estimation, while being more resilient to noisy gradients [13,14]. MobileNetV1 with goose optimization empowers the proposed AI framework by ensuring a highly accurate classification of tropical cyclones, contributing to farm-level disaster readiness.

5. Results and Discussion

The AI framework was fine-tuned during training and validation with hyper-parameters, such as 50 epochs, a learning rate of 0.0001, and a batch size of 32. The model was integrated with a goose optimizer to optimize the performance of the four distinct classes of cyclones. Figures 2(a) and 2(b) show the training and validation accuracies and loss plots, respectively.

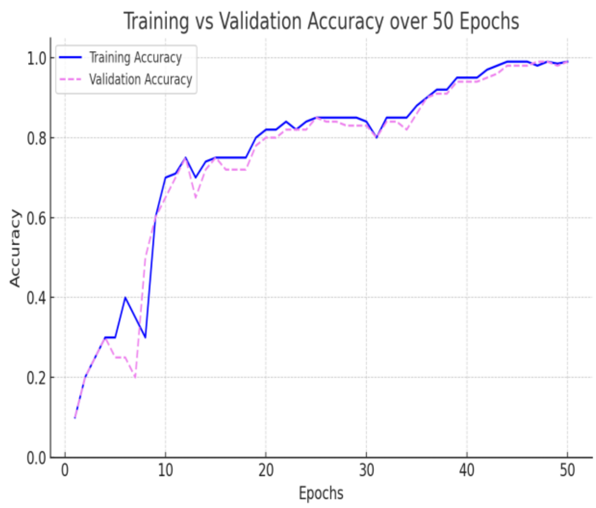

Figure 2(a) **Training and validation Performance: Accuracy**

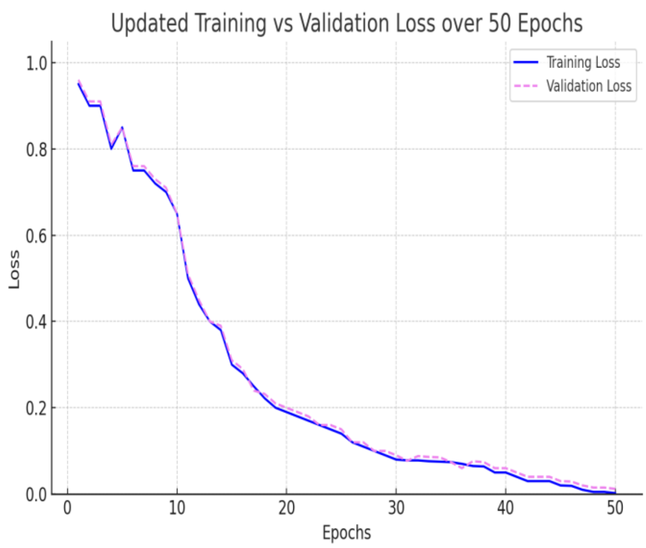

Figure 2(b) **Training and validation Performance: Loss**

The accuracy curves showed a consistent upward trend, indicating effective learning and generalization. The loss curves exhibit a steady and synchronized downward trend, which is an ideal indicator of a well-performing process. Overall, the training and validation performances reflect efficient model training, supported by the goose optimizer. The overall and class-wise performance of the AI framework on the test data are presented in Tables 3 (a) and 3(b), respectively. The framework achieved an accuracy of 98.33%, precision of 98.36, Recall, F1 score of 98.33, and AUC of 100%.

Table 3(a) **Overall Performance**

Accuracy	Precision	Recall	F1 score	AUC
98.33%	98.36%	98.33%	98.33%	100%

Table 3(b) **Class-wise performance**

Class	Precision	Recall	F1 Score
Class 1	98.36%	100.00%	99.17%
Class 2	96.77%	100.00%	98.35%
Class 3	98.31%	96.67%	97.48%
Class 4	100.00%	96.67%	98.30%

An overall accuracy of 98.33% reflects a high level of accuracy across all classifications, and the precision (98.36%), recall (98.33%), and F1 score (98.33%) indicate a well-balanced model that maintains high specificity and sensitivity. In addition, an AUC of 100% confirmed the model's ability to distinguish between all cyclone classes with perfect discriminatory power. Regarding class-wise performance, classes 1 and 2 exhibit recall (100.00%), indicating that the model successfully identifies all instances belonging to these classes. Class 1 also achieved 98.36% precision, while lass 2 achieved 96.77%, reflecting minimal false positives. The resulting F1 scores of 99.17% for class 1 and 98.35% for class 2 indicate a near-perfect classification performance. Classes 3 and 4 showed slightly lower recall values (96.67% each), and their precision remained high (98.31% for class 3 and 100.00% for class 4). The Figure 4 shows confusion matrix of the proposed model.

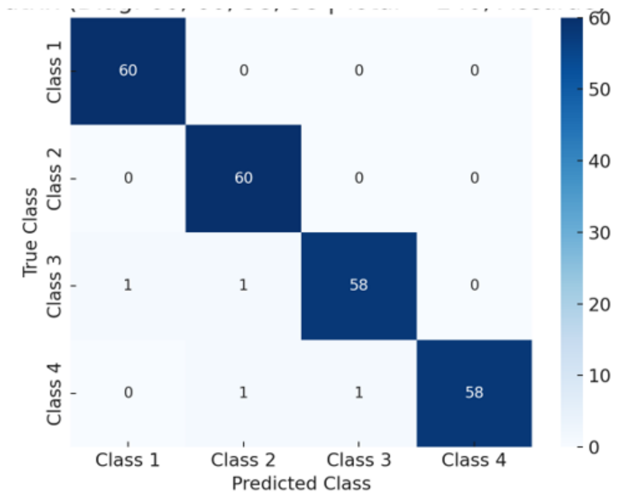

Figure 4 **Confusion Matrix**

Out of a total of 240 samples, the model classified 236 cyclone images perfectly, as indicated by diagonal elements, and only four images were misclassified (off-diagonal elements). Consequently, the accuracy is 98.33%. In addition, classes 1 and 2 were classified with perfect accuracy (100%), class 3 had two misclassifications, and class 4 recorded two misclassifications. The low number of off-diagonal entries reflects strong generalization capabilities. The mathematical equations for all metrics are given in (1-4) [15].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1\ Score = \frac{2TP}{2TP + FP + FN} \quad (4)$$

TP = actual positive; TN = actual negative
FP = false positive; FN = false negative

The ROC curve displayed in Figure 4 represents the performance of a multi-class classifier in identifying the four cyclone categories. The model achieved an AUC of 100%, indicating perfect precision and recall, and no FP or FN were recorded.

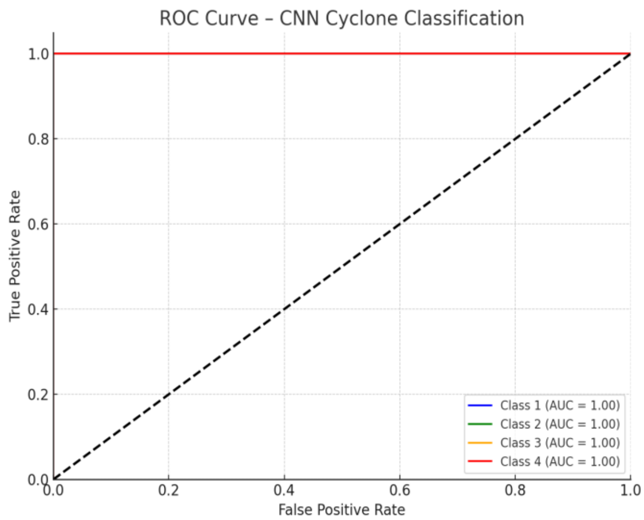

Figure 5 **ROC Curves**

The performance of the proposed AI-powered framework with various architectures and optimizers is presented in Table 4. A bar graph representation is presented in Figure 5 & 6.

Table 4 **Comparison of the Proposed AI Powered**

Frame Work with Various Pre-trained CNN Models and Optimizers

Architecture	Optimizer	Accuracy in %
MobileNet	Adam	90.25
MobileNet	Sea Horse	91.24
MobileNet	SGD	92.12
MobileNet	Goose	98.33
VGG16	Adam	65.21
VGG16	Sea Horse	55.50
VGG16	SGD	60.36
VGG16	Goose	71.22
VGG19	Adam	81.24
VGG19	Sea Horse	87.21
VGG19	SGD	82.00
VGG19	Goose	89.27
Resnet	Adam	40.25
Resnet	Sea Horse	45.68
Resnet	SGD	49.52
Resnet	Goose	52.12

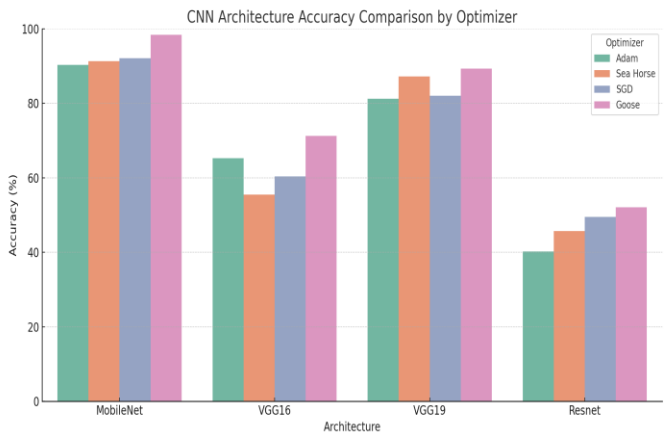

Figure 6 Bar-graphs: Comparison of the proposed AI powered frame work with various pre-trained CNN models and optimizers

In the present work, the performances of the four different CNN architectures, MobileNet, VGG16, VGG19, and ResNet, were computed using four optimizers: Adam, Sea-Horse, SGD, and Goose. According to Table 4, MobileNet with the goose optimizer outperforms other architectures across all optimizers, achieving an accuracy of 98.33%. The results confirm that the proposed AI-powered cyclone classification framework using MobileNetV1 and goose optimizer excels in classifying tropical cyclones, thereby reinforcing its suitability for deployment in real-time agro-climatic advisory systems to support climate-resilient farming.

Conclusion

The present work proposes a robust and efficient AI framework aimed at enhancing climate-resilient farming by accurately classifying four distinct classes of tropical cyclones using satellite imagery. The integration of MobileNetV1 with the Goose optimizer outperformed it with an accuracy of 98.33% and an AUC of 100%. The superiority of the framework is further compared with other pre-defined CNN architectures, such as VGG16, VGG19, and ResNet, combined with different optimizers. In subsequent stages, this cyclone classification framework can be expanded to encompass additional climate-related agricultural challenges.

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