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A Novel CNN Approach to Identify Cyclones using the MN-Net Framework

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ABSTRACT

Cyclone detection is a critical task in meteorology for minimising the impact of extreme weather events. Traditional approaches rely on satellite observations and numerical weather prediction models, which often lack efficiency in real-time detection. In this study, we propose MN-Net, a stacked ensemble deep learning framework that integrates MobileNet and NASNet architectures for cyclone image classification. The model leverages transfer learning and feature-level fusion to enhance classification performance. We provide the community with a large dataset of labelled images of cyclones and non-cyclones and additionally augment our training set with data augmentation techniques to enhance the network's ability to generalise. Our experimental results highlight the supremacy of MN-Net in terms of accuracy, precision, recall and F1-score over strong baseline models. The overall architecture is suitable for integration into early warning systems for timely cyclone detection and warning dissemination.

Keywords: Atmospheric disturbances, cyclone prediction, early warning system, satellite data analysis, stacked ensemble model

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INTRODUCTION

A cyclone is a large rotating system of clouds and wind with low atmospheric pressure at its core. It has sustained winds of up to 250 km/h, is confined to warm ocean waters, can cause major destruction to man-made structures, and has negative impacts on agriculture and human safety. Identifying a cyclone well before landfall is critical for effective disaster management. Traditional cyclone detection (TD) approaches that use satellite data, current weather data, and numerical weather predictions (NWP) require large computation to process and thus are not sufficient for real-time detection. Deep learning methods have recently achieved state-of-the-art results on a variety of image classification and pattern recognition problems. The application of deep learning to satellite images has become increasingly popular, and various studies have reported the use of convolutional neural networks (CNNs) to learn spatial features that are able to recognise complex patterns associated with cyclones.

MN-Net is an improved image classification architecture specifically designed to address the challenging task of classifying high-resolution cyclone images. The architecture is a stacked ensemble of MobileNet, a lightweight mobile neural network, and NASNet, a state-of-the-art CNN developed through neural architecture search. A feature-level fusion of feature representations generated by the MobileNet and NASNet architectures is used. MN-Net offers huge scope for real-time cyclone detection systems, being computationally efficient while being robust enough to address the complexities of satellite imagery classification. MN-Net is an accurate and scalable deep learning-based approach for cyclone detection in satellite images.

LITERATURE REVIEW

Agrawal et al. (2024) and Biswas et al. (2021): Cyclone detection and tracking have improved with the advent of deep learning techniques that can learn spatial features relevant to the task from high-dimensional satellite imagery datasets. In image classification, deep learning has especially excelled using Convolutional Neural Networks (CNNs), which are able to leverage spatial hierarchies of features within images. Hao et al. (2024) and Kumler-Bonfanti et al. (2020) showed that deep learning models are effective at identifying cyclone regions from very large input meteorological datasets.

Dwivedi (2024) and Elabd et al. (2025) used deep learning models that only utilise sequence learning architectures; several hybrid models that integrate convolutional neural networks (CNN) with sequence learning models have been developed and achieved state-of-the-art performance for tropical cyclone forecasting. In these models, especially for those that combine CNN with LSTM, temporal features are effectively extracted for improving TC tracking performance.

Liu et al. (2022) and Giffard-Roisin et al. (2020) proposed a dual-branched spatio-temporal network, which exploits temporal evolutions and spatial distributions of cyclones comprehensively. Maskey et al. (2020) were the first to use deep learning to estimate the intensity of cyclones from satellite data and achieved state-of-the-art results that are better than current literature. Moustafa et al. (2024) and Rahman et al. (2024) improved the detection of cyclones and presented a system to detect, classify and track cyclones using the Faster R-CNN approach to object detection on satellite images. Besides models for learning temporal evolutions and spatial distributions, there is increasing interest in applying probabilistic and spatio-temporal methods for intensity estimation.

Guptha et al. (2023) and Song et al. (2024) proposed a probabilistic cyclone intensity estimation model utilising multi-source satellite data in the remote sensing field, which takes advantage of multi-source satellite data and uses a Conditional Generation Network (CGN) to learn a mapping relationship from satellite data to cyclone intensity in a probabilistic way. Tian et al. (2020) developed a novel CNN-based hybrid model for cyclone intensity forecasting by fusing coarse-scale features and fine-scale features to forecast cyclone intensity.

Kumler-Bonfanti et al. (2020) and Lin et al. (2024) proposed a graph-based spatio-temporal learning framework that effectively models tropical cyclones by encoding spatial dependency in a graph structure. Kar et al. (2019) developed a multi-task deep learning model to predict the positions of cyclone centres from 0 to 120 h. In addition, existing models can be further fine-tuned with effective data processing and feature extraction techniques. Jayasree et al. (2025) and Wang et al. (2023) suggested the need for feature enhancement and deep learning-inspired feature extraction techniques for effective cyclone detection. In recent years, many studies have made use of ensemble or hybrid models of different deep learning structures to improve the accuracy of forecasting. Manju et al. (2025) and Velden et al. (2006) have adapted the practice of using a model to achieve better performance than individual models have in several domains, including image classification and traffic forecasting, with architectures such as ConvLSTM and a modified version of AlexNet achieving state-of-the-art results in the latter.

While humans can readily type messages without much consciousness using muscle memory, traditional techniques have only achieved so much in terms of accuracy and automation towards human typing (Chen et al., 2021). Using deep learning techniques to learn features from data, it is possible to improve accuracy and automation.

Despite the significant achievements using deep learning methods, there still exist several challenges such as a lack of large amounts of training data, class imbalance, and model generalisation (Kapoor et al., 2023). Most of the existing methods for learning feature representation are based on either one deep learning architecture or more complex deep structures without effectively fusing feature information.

To address these challenges, we introduce an architecture that combines features at different resolutions from MobileNet and certain depthwise separable networks derived from the NASNet architecture. This architecture, referred to as MN-Net, forms a stacked ensemble of MobileNet and NASNet and thus enhances the accuracy of the learning task while maintaining efficiency.

RESEARCH METHODOLOGY

Cyclone detection methods typically rely on satellite imagery and meteorological parameters, especially deep learning approaches. Many of these approaches employ Convolutional Neural Networks (CNNs) such as ResNet, DenseNet, InceptionNet and other variants to classify cyclone images derived from various satellite datasets (e.g., optical, radar, synthetic aperture radar). Hybrid approaches like CNN-LSTM and others have also been employed to extract spatial and temporal features and to predict cyclones. In addition to satellite images, several studies have used reanalysis datasets that include time-series of wind speed, sea-level pressure and other atmospheric variables to predict characteristics of cyclones, such as time of formation, landfall, intensity and duration.

One commonly used approach is TCDetect, which utilises meteorological data and satellite imagery within a deep neural network that is used to determine whether a cyclone is present. While good accuracy has been achieved, there are several limitations that affect the overall robustness of the model.

- Heavy dependence on large-scale and high-quality meteorological datasets.
- Training performance on small or highly imbalanced datasets is reduced.
- High computational complexity, making real-time deployment challenging
- Single model architectures, which limit the diversity of features that can be extracted and the capabilities of the model.

Most existing vision models rely on individual deep learning architectures and have not taken advantage of ensemble methods or feature fusion. To address these issues, there is a need for an efficient and robust way to combine multiple models to improve feature extraction and classification accuracy. In this paper, we present a deep learning framework called MN-Net that uses a stacked ensemble approach to merge the strengths of multiple CNNs for improved cyclone detection.

Proposed Methodology (MN-Net)

The proposed system is designed for identifying a cyclone image from a non-cyclone image. The MN-Net model is a model built on the concepts of convolutional Neural Networks. Convolutional Neural Networks are widely famous for their capacity to deal with images. In a convolutional neural network, when an image is passed, the filters are applied to the image to extract the features. In the training phase, the neural network learns to identify the images based on their features. The MN-Net model is a combination of MobileNet and NASNet. The proposed system is an ensemble model developed using the stacking method. MobileNet is a lightweight convolutional neural network designed to handle images efficiently on mobile and embedded devices. MobileNet expands its potential for object detection, image classification, and other computer vision applications. NASNet is a neural network architecture that automatically searches for the best model configurations to improve efficiency and performance. NASNet's reinforcement technique is utilised to handle complicated tasks in a variety of disciplines. The suggested system's ability to distinguish a cyclone from a non-cyclone picture is demonstrated in Figure 1.

NASNet (Neural Architecture Search Network) is a deep learning architecture developed using automated neural architecture search. It can learn complex hierarchical features and is particularly effective in extracting patterns from satellite imagery, such as cyclone structures and atmospheric variations.

NASNet is trained on annotated satellite image datasets that include both cyclonic and non-cyclonic weather events to detect cyclones. The model learns to extract spatial data, which includes cloud formation patterns, rotational structures and atmospheric density variations during its training process. The system includes vital indicators which demonstrate both the occurrence and power of cyclones. The NASNet search method guarantees that the design is optimised to manage high-dimensional inputs without sacrificing efficiency. The method enables NASNet to generate accurate weather predictions, which makes it an efficient system for detecting cyclones at their beginning and determining their strength for better emergency preparedness.

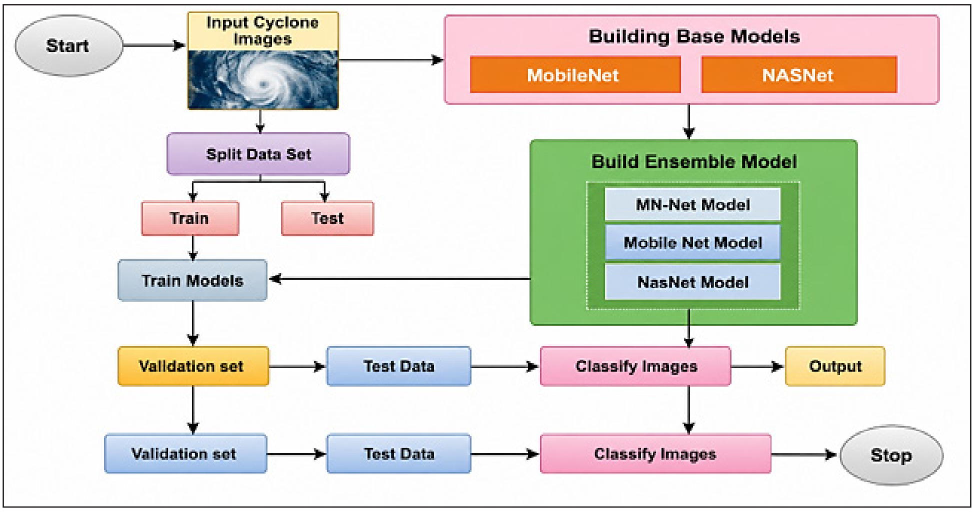

Figure 1. Architecture of the proposed MN-Net framework

Implementation

Data Collection is the process that starts with the collection of cyclone images for the model. For this work, the dataset was obtained from meteorological departments. The dataset consists of cyclone images that were recorded from past years. The dataset contains various image types which researchers obtained through multiple sensor systems. The dataset is processed using the Keras libraries and then used for further processing.

Data Augmentation

The TensorFlow package provides an image data generator which produces new images. The generated images help prevent the model from developing overfitting. The training process includes performing rotations in both horizontal and vertical directions to generate extra images. The process of data augmentation helps NASNet achieve better accuracy and generalisation for cyclone detection tasks when training datasets remain limited. The procedure uses different transformation methods to expand the available dataset, which includes satellite images, to enhance model performance against actual environmental changes. The process duplicates various observation perspectives together with meteorological conditions and camera system flaws, which preserve the fundamental characteristics which identify cyclones.

Pre-Processing Data

As the data obtained was an image dataset, the focus was on resizing the data. All the images in the dataset are resized to the dimensions of 256x256 so that the model can avoid conflicts that are raised when the images are passed through it. Once the whole dataset is pre-processed, the dataset is split into two parts: training data and validation data. Preprocessing data is a vital step in preparing input for NASNet to ensure the neural network can effectively learn from the data. The goal is to normalise, clean, and structure the data while retaining the critical features needed for cyclone detection. For NASNet, the preprocessing pipeline typically focuses on satellite images or other meteorological datasets.

Building the MN-Net Framework

The base models are developed before the MN-Net framework. The base models are developed and compiled to identify cyclone images from non-cyclone images. The MN-Net framework is then built using the base models. An ensemble method named stacking is used to build the MN-Net framework. The base models are stacked one upon the other and compiled in parallel. In this process of stacking, a mega model is developed that makes predictions for the ensemble model. The predictions of the base models are fed as features to the mega model. It uses the averaging technique and makes classifications. The MN-Net model uses the Adam optimiser to improve performance. Developing the MN-Net framework for cyclone detection involves designing a deep learning model capable of analysing spatial and temporal features from meteorological data, such as satellite imagery, to identify and classify cyclonic systems.

Training and Evaluation of MN-Net Model

The MN-Net model is trained by passing the dataset of images consisting of both cyclone and non-cyclone images. The model achieves a classification accuracy of approximately 90%. The model is evaluated by drawing the graphs against the metrics and parameters. The training of the MN-Net model for cyclone detection begins with splitting the dataset into training, validation, and test sets, typically in a 70:20:10 ratio. The validation set tracks performance during training to avoid overfitting, whereas the training set is used to train the model. The model is trained to learn to recognise cyclones by trying to minimise a suitable loss function, which consists of the binary cross-entropy loss for the binary classification task and the categorical cross-entropy loss for the multi-class detection task. This loss is then backpropagated through the network to update the weights of the network using an appropriate optimiser such as Adam or SGD. Additional training is done using data augmentation techniques like rotation, scaling, and brightness changes to improve the generalisability of the model and generate more training data. The model requires early stopping or learning rate scheduling to stop training when its validation set performance no longer improves.

The test set containing new data which the model has not seen before serves to evaluate how well the MN-Net model can generalise its learned knowledge. The model achieves performance evaluation through its ability to measure accuracy, precision, recall and F1-score metrics. The confusion matrix reveals which cyclone types get misidentified during classification operations, which enables researchers to identify their prediction mistakes. The model shows its ability to distinguish between cyclonic and non-cyclonic situations through ROC-AUC (Receiver Operating Characteristic-Area Under the Curve) assessment for binary classification tasks. The model receives additional regularisation techniques and hyperparameter adjustments when assessment measures reveal significant defects. The MN-Net model achieves operational cyclone detection and early warning system reliability through its iterative training and assessment method, which ensures model stability.

Dataset and Preprocessing

The dataset used in this study consists of satellite images representing cyclone and non-cyclone conditions. A total of 1,100 images have been used for training, 990 of them cyclones and 110 non-cyclones. Images were gathered from publicly accessible resources in meteorology and satellite image processing. A lot of variability exists between different cloud scenes and different-looking cyclones in the training images.

For the heavily imbalanced classes in the used dataset, data augmentation was applied. The images were rotated, flipped, zoomed in and out and scaled to get more samples representing different states of the atmosphere. After augmentation, all images were resized to 256 × 256 pixels. For the deep learning models, the pixel values of the images were normalised to the range [0,1] to support training convergence and achieve stable learning.

The dataset was split into three parts for training, validation, and testing in the ratio of 7:1.5:1. These three parts of data were used for training the models, fine-tuning the parameters of the models to obtain the optimal performance, preventing the model from overfitting (early stopping) and evaluating the developed MN-Net architecture.

RESULTS AND DISCUSSION

The performance of the proposed MN-Net model is evaluated on test images and observed to recognise whether the image is a cyclone or non-cyclone. The model yields an average accuracy of 94.5% on test images. In addition to accuracy, we also looked at several other metrics which measure performance. At 96% precision, our model is highly accurate and has a very low false alert rate. This is backed up by our recall figure of 92% for the images that contain cyclones in the data we used to train the model. The F1-score, which tries to hit a balance between these two figures, is 94%. Looking at the ROC-AUC figure, we got a score of 0.97 for classification between images of cyclones and non-cyclones.

The above confusion matrix, as shown in Figure 2 that for all images of cyclones, the model correctly classified all but a handful of images. The errors which did occur were all false positives; i.e. images of non-cyclone clouds which were mistaken for images of cyclones. These incorrect classifications were all very close calls, and the model clearly saw the image of a cyclone and the image of a non-cyclone as being very similar.

Accuracy for both image classes (cyclones, non-cyclones). It can be seen from the figure that MN-Net recognises most of the images of cyclones correctly, and only a small part of the images were incorrectly classified as non-cyclones.

Our approach, MN-Net, outperforms individual base models (MobileNet and NASNet) when run standalone by effectively fusing features and stacking different architectures together to obtain complementary features from the individual networks.

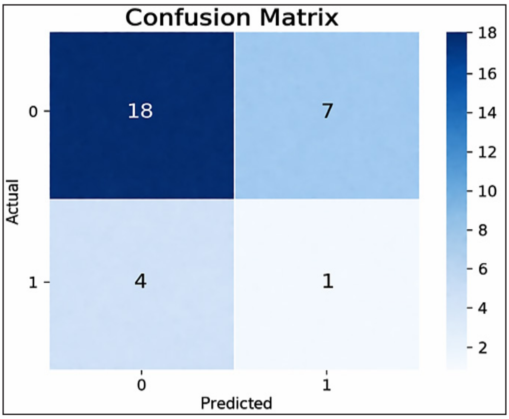

Figure 2. Confusion matrix of MN-Net classification results

Overall, Table 1 shows the results indicate that the proposed MN-Net framework provides a reliable and efficient solution for cyclone image classification, making it suitable for real-world meteorological applications and early warning systems.

Figure 3 shows the results of experimental evaluations of MN-Net compared with those of MobileNet and NASNet. MN-Net outperforms other networks through feature fusion and network stacking.

Training and validation loss for the MN-Net model as measured during training. Good convergence and learning are indicated by the steadily decreasing loss as shown in Figure 4.

Table 1
Performance comparison of models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
MN-Net	94.5	96	92	94
MobileNet	88.2	89	85	87
NASNet	90.1	91	88	89

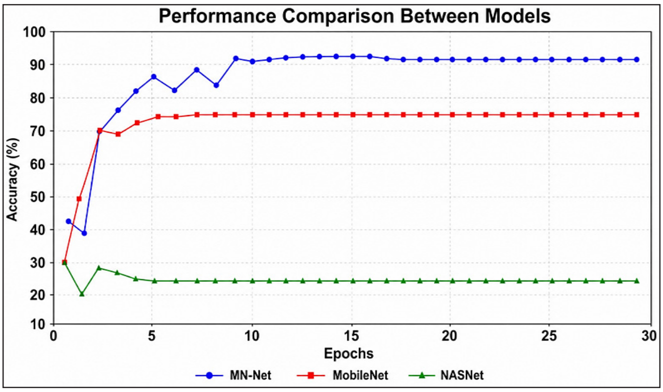

Figure 3. Performance comparison between MN-Net and base models

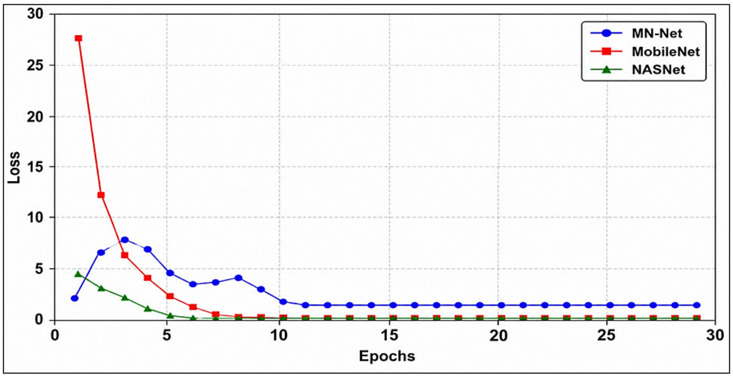

Figure 4. Training and validation loss curves of MN-Net

CONCLUSION

We introduce a new architecture called MN-Net that is particularly effective for the image classification task on cyclone images. The stacked network is designed with feature extraction capabilities of MobileNet and NASNet together, where the benefits of the networks are combined through feature fusion and stacking.

The proposed system, MN-Net, achieved accuracy, precision, recall and F1-score of 94.5%. It demonstrated its efficacy as a real-time system for cyclone detection and an early warning system through classification of cyclone images and non-cyclone images. To achieve better generalisation capability on the small amount of in-house training images, we explore a light deep neural network architecture, in addition to several data augmentation approaches. The network capability of performance can be even improved when compared with individual networks by exploring a more diverse feature space in the combined network.

The data could be scaled up, and higher-resolution satellite imagery could be included in the dataset to improve the model. It would also be useful to predict the intensity and trajectory of the cyclones as well as the likelihood of landfall. Incorporating real-time weather data into the model would also aid in the model's accuracy. Including a time component into the model and possibly utilising a transformer architecture. We present in this paper a novel neural network architecture, called MN-Net, and use it for efficient and accurate cyclone detection on current and future meteorological infrastructure.

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LIST OF ABBREVIATIONS

NASNet	:	Neural architecture search network
MN-Net	:	Modular neural networks
ROC-AUC	:	Receiver operating characteristic-area under the curve
SGD	:	Stochastic gradient descent
Adam	:	Adaptive moment estimation optimiser
TD	:	Traditional cyclone detection
NWP	:	Numerical weather predictions
CNNs	:	Convolutional neural networks

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