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Tropical Cyclone Identification and Alert System using AlexNet and Deep CNN

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Abstract
Tropical cyclones (TCs) are catastrophic weather occurrences that can inflict massive damage in coastal regions across the world. Weather nowcasting, which is the weather forecast for a short time period, is one of the most challenging topics in meteorology. Weather radar and satellite are essential technologies for nowcasting, but issuing nowcasting warnings based on radar and satellite data is a difficult process. This proposed approach is of a deep learning approach for TC identification from aerial imagery, which includes a Deep Convolutional Neural Network of Alex-Net architecture as the classifier.

Keywords: Convolutional neural network (CNN), Deep learning, AlexNet, Deep Convolutional neural network (Deep- CNN), Tropical cyclone (TC), Satellite Images

Introduction
Tropical Cyclone (TC) [1] is described as the quick rotation of powerful storms with a low-pressure core, calm winds, a closed low-level atmospheric circulation, and a spiral configuration that delivers heavy rainfall. Tropical cyclones are classified as typhoons, hurricanes, cyclonic storms, tropical storms, cyclones, and tropical depressions based on their location and power.

The term "tropical" refers to the geographical origin of systems that originate solely in tropical oceans.
The term "cyclone" refers to winds that revolve in a circle by whirling around a clear central eye while blowing counter-clockwise in the Northern Hemisphere and turning clockwise in the Southern Hemisphere. The currents in the northern and southern hemispheres flow in opposing directions due to the Coriolis phenomena.

Tropical cyclones often originate over bigger bodies of relatively warm water. TCs appear to have a greater impact on coastal areas. Stronger winds, higher storms, and surges cause extensive damage to coastal agricultural fields, houses, and plantations.

Cyclones are one of the most destructive natural disasters, causing severe damage to human lives and infrastructure. Early detection and classification of cyclones can help authorities prepare and execute timely evacuation plans, reducing the impact of these catastrophic events.
There have been several tropical cyclones that have impacted India in recent years like:

- Cyclone Yaas (May 2021) - Cyclone Yaas made landfall in the eastern Indian state of Odisha on May 26, 2021. It caused widespread damage and flooding in the region. [2]
- Cyclone Amphan (May 2020) - Cyclone Amphan hit the eastern Indian states of West Bengal and Odisha in May 2020. It was one of the strongest cyclones to hit the region in decades, causing widespread damage and loss of life.[3]
- Cyclone Fani (May 2019) - Cyclone Fani made landfall in the eastern Indian state of Odisha in May 2019. It was one of the strongest storms to hit India in recent years, causing widespread damage and loss of life. [4]
- Cyclone Nivar (November 2020) - Cyclone Nivar hit the southern Indian states of Tamil Nadu and Puducherry in November 2020. It caused widespread damage and flooding in the region.[5]

Literature Review

Some of the related works in detection of cyclone in satellite images are discussed here.

- Convolutional Neural Networks (CNNs)

The study by Y. Wang et al. (2019) [6] proposes a deep learning-based approach for the detection and tracking of tropical cyclones using an AlexNet-based CNN. The model is trained on satellite imagery and is shown to outperform traditional methods in terms of accuracy and computational efficiency.

The authors [7] propose a deep CNN-based approach for the detection and classification of tropical cyclones. The model is trained on both visible and infrared satellite imagery and is shown to achieve high accuracy rates.

[8] proposes a deep CNN-based approach for automatic identification and intensity estimation of tropical cyclones. The model is trained on satellite imagery and is shown to achieve high accuracy rates for both identification and intensity estimation.

Another study by P. E. Mantilla et al. (2020) [11] proposes a deep learning-based approach for the identification of tropical cyclones using synthetic imagery. The model is trained on a dataset of simulated tropical cyclones and is shown to achieve high accuracy rates for detection.

- Pattern Recognition

N. Sharma et al. (2017) explores the use of machine learning techniques, specifically decision trees and random forests, for the identification of tropical cyclones from satellite imagery in “Tropical Cyclone Identification using Machine Learning Techniques” [12]. The models are trained on several image features, including texture, color, and shape, and achieve high accuracy rates.

“Tropical Cyclone Eye Feature Recognition using Convolutional Neural Networks” by C. Qiu et al propose a CNN-based approach for the recognition of the eye feature of tropical cyclones [13]. The model is trained on a dataset of satellite images and achieves high accuracy rates for eye feature recognition.

Other algorithms include Fuzzy Pattern Recognition techniques like in [14] by R. Saravanan et al, or a combination of CNN's and RNN's for pattern tracking in [15] by C. Wang et al.

- **System Architecture**

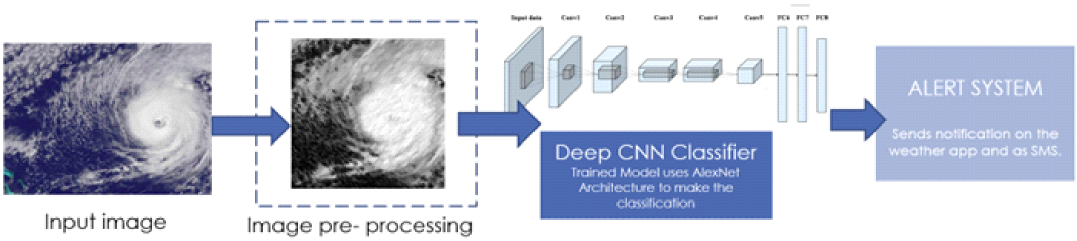

Figure 1. System Architecture of TC Identification and Alert System

The system architecture shows the overall workflow of the project. Here, we use the aerial image uploaded by user. The system performs the preprocessing steps on the image. Then the preprocessed images are fed to the AlexNet it extracts the features from different layers. After extraction of the features from the image, it is fed to the deep-CNN. It classifies the image and identifies if the image has cyclone or not.

Methodology

Development and deployment of this TC identification and Alert System has workflow that consists of three important modules. The suggested identification method applies CNN's pre-trained AlexNet [16] architecture to user uploaded image. This approach is well in agreement with the machine learning lifecycle. The machine learning lifecycle is a systematic iterative process train, test, and deploy a model to develop an optimized models ready for integration into production systems and targeted end-user consumption

- Image Pre-Processing

Image pre-processing is a crucial step in cyclone classification. In this step, the images of cyclones are resized to a smaller size of 28x28x1 to reduce the computational complexity. Additionally, the images are changed from color to black and white using Python packages such as PIL and OpenCV2. The black and white conversion helps to simplify the image data and reduce the dimensionality. This simplification can help the machine learning model to focus on important features, such as the shape and structure of the cyclone, instead of color. Overall, image pre-processing is an essential step in cyclone classification, as it helps to improve the accuracy of the model by enhancing the quality of the input data..

- Feature Extraction & Deep CNN Classification

Feature Extraction is necessitous and task-specific. It plays a crucial role in finding patterns and learn complex features from input images for the classsification of the images. The AlexNet model, which consists of eight convolutional layers and three fully connected layers, is used for feature extraction, while the deep CNN model is used for binary classification.

The cropped, resized image with grayscale filter is then feed into for prediction on which class it belongs, cyclone or not_cyclone. The AlexNet trained model is modified and customized for this project where every layer has different dimensions than the original.

The architecture consists of the following layers:

Convolutional Layer 1: The first layer is a convolutional layer with 96 filters of size 11x11, using a stride of 4, and ReLU activation function. This layer takes the input image with a shape of (28, 28, 1) and produces feature maps of size (55, 55, 96).

Max Pooling Layer 1: This layer applies max pooling with a pool size of 2x2 and a stride of 2. This reduces the spatial size of the feature maps to (27, 27, 96).

Convolutional Layer 2: The second layer is a convolutional layer with 256 filters of size 5x5, using a stride of 1, and ReLU activation function. This layer uses padding to preserve the spatial size of the feature maps, producing output feature maps of size (27, 27, 256).

Max Pooling Layer 2: This layer applies max pooling with a pool size of 2x2 and a stride of 2. This reduces the spatial size of the feature maps to (13, 13, 256).

Convolutional Layers 3-5: These layers are convolutional layers with 384, 384, and 256 filters of size 3x3, using a stride of 1, and ReLU activation function. All three layers use padding to preserve the spatial size of the feature maps.

Max Pooling Layer 3: This layer applies max pooling with a pool size of 1x1 and a stride of 2. This reduces the spatial size of the feature maps to (6, 6, 256).

Flatten Layer: This layer flattens the output of the previous layer into a one-dimensional array of size 9216.

Fully Connected Layer 1: This layer is a fully connected layer with 4096 neurons and ReLU activation function.

Dropout Layer 1: This layer randomly drops 50% of the neurons to prevent overfitting.

Fully Connected Layer 2: This layer is a fully connected layer with 4096 neurons and ReLU activation function.

Dropout Layer 2: This layer randomly drops 50% of the neurons to prevent overfitting.

Output Layer: This layer is a fully connected layer with 2 neurons and softmax activation function, producing the final output of the model.

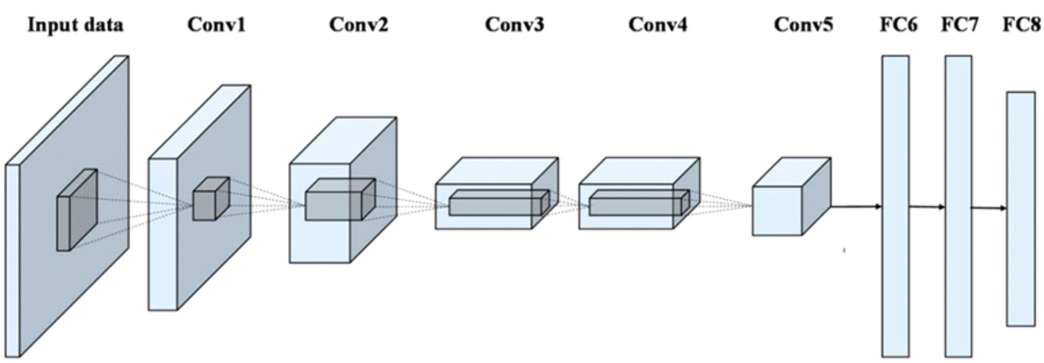

Figure 2 AlexNet Architecture

The formulae used in the convolutional and max pooling layers are as follows:

- Convolution:
- Max Pooling:

Where input_size is the spatial size of the input feature maps, filter_size is the spatial size of the filters, padding is the number of pixels added to the borders of the input feature maps, stride is the number of pixels the filter is moved at each step, and pool_size is the spatial size of the pooling window.

The deep CNN model is trained using the extracted features as input and is able to accurately classify cyclones based on their intensity. This approach has shown promising results in cyclone classification, with high accuracy and efficiency in detecting cyclones of different intensities.

- Alert System

The aim of the alert system is to provide timely and accurate information to the public about an impending tropical cyclone. The system helps to alert people in the affected areas to take necessary precautions and make preparations to minimize the damage and loss of life.

This is implemented by using Twilio [17] in Python that sends SMS alerts to recipients in the affected areas when the classifier from before classifies the uploaded image as “Cyclone”.

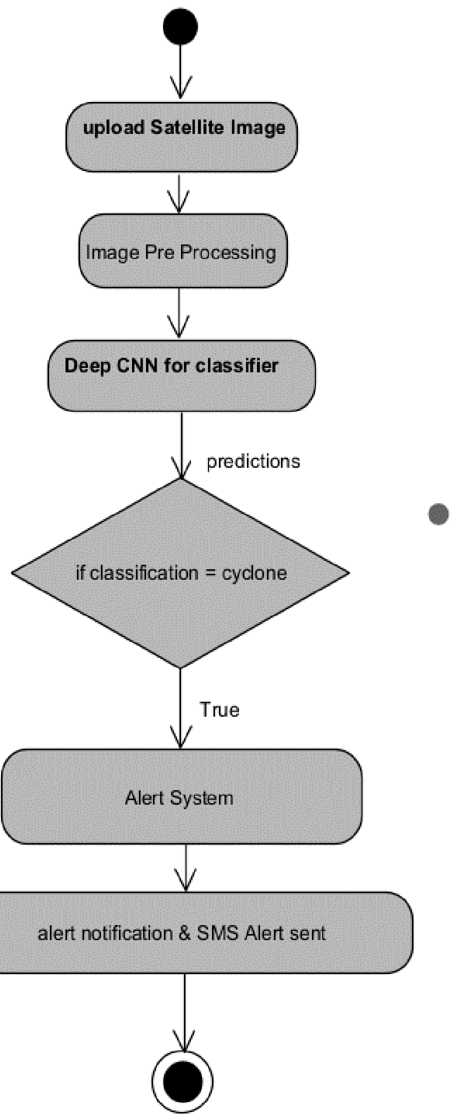

Figure 3 Cyclone Identification & Alert System Process Flow

Conclusions

The Tropical Cyclone Identification and Alert System shown significant promise for effectively detecting and monitoring tropical storms utilizing deep learning algorithms such as AlexNet and Deep CNN. These models can extract significant elements from satellite pictures and categorize them into numerous categories by applying the capability of convolutional neural networks. Several advantages of this methodology over typical tropical cyclone identification methods include: B. Threshold-Based Techniques and Human Interpretation. It can be time intensive and prone to errors. Deep learning algorithms may be used to automate the identification process, decreasing human analysts' burden and speeding up response times. Furthermore, the development of efficient tropical cyclone identification and warning systems using satellite imagery has important implications for disaster management and risk reduction. Early detection and accurate tracking of tropical cyclones can help evacuate vulnerable populations, prepare emergency response teams, and minimize loss of life and property

Future Enhancement

Additional enhancements could be incorporating additional data sources such as weather radar and ocean buoys to provide more information for the system. This would improve its ability to predict the trajectory and intensity of storms. Another enhancement could be to include a forecasting component that analyses historical data and current weather patterns to predict future storm behaviour. The system could also be improved by providing real-time analysis of tropical cyclones as they develop, using advanced computing techniques and a high-speed data processing system. Integrating the system with emergency response systems would provide early warning and evacuation alerts to at-risk populations, requiring collaboration between meteorologists, emergency responders, and government agencies. Finally, expanding the system's geographic coverage to remote or under-served regions would require the deployment of additional sensors and satellite systems. Overall, these enhancements could significantly improve the automated tropical cyclone identification system's effectiveness and help to mitigate the damage caused by tropical storms.

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