

Tropical Cyclone Classification And Intensity Estimation Based On Image Processing And Convolutional Neural Network

Darshan M¹, Farhan Ulla Baig², Hruthik S R³, Mohal Gowda M P⁴

^{1, 2, 3, 4} Dept of Computer Science & Engineering

^{1, 2, 3, 4} Mysuru Royal Institute of Technology, Mandya, Karnataka, India

Under the guidance of Prof. Kalathma M K, Dept. of CSE, MRIT, Mandya

Abstract- Tropical cyclones are among the most destructive natural hazards, producing extreme winds, heavy rainfall with flooding and damaging storm surge along low-lying coasts. Estimating their intensity quickly and objectively from satellite imagery is therefore central to early warning, yet traditional methods such as the Dvorak technique depend on manual and subjective interpretation. This paper presents a hybrid system for tropical cyclone classification and intensity estimation based on image processing and a Convolutional Neural Network (CNN). Preprocessed infrared satellite images are passed to two parallel branches: a CNN that estimates intensity as High, Medium or Low, and an image-processing pipeline that classifies severity as Severe, Moderate or Normal from cloud structure and eye pattern. A fusion layer based on weighted voting, or a stacked meta-classifier, combines both outputs into a single, higher-confidence class. The system is implemented in Python using TensorFlow/Keras, OpenCV and scikit-learn, and is demonstrated through a web interface in which a user uploads an infrared image and receives the individual and fused predictions along with confidence scores.

Keywords- Tropical cyclone, intensity estimation, convolutional neural network, image processing, infrared satellite imagery, decision fusion.

I. INTRODUCTION

A tropical cyclone (TC) is an intense circular storm that originates over warm tropical oceans. It is characterized by low atmospheric pressure and heavy rain, and its winds exceed 119 kmph. When such a system reaches the coast it can bring extreme winds, flooding from heavy rainfall and storm surge that inundates low-lying areas, so a timely and accurate assessment of its strength directly affects how much warning coastal communities receive.

Over open oceans, where direct measurements are scarce, satellite imagery is the main source of observations. In infrared images the structure of a cyclone—the eye, the eyewall and the spiral rainbands—is clearly visible, and it is exactly this structure that both image-processing and CNN-

based methods read from satellite imagery to judge intensity. Traditionally, analysts have interpreted these cloud patterns by hand using methods such as the Dvorak technique. Such manual methods are time-consuming and subjective, and the result can vary with the judgement of the person doing the analysis.

Deep learning offers an alternative. A CNN can learn intensity-related features directly from images, while classical image processing extracts interpretable information about cloud structure and eye pattern. Each approach has its own strengths and weaknesses, and combining the two is a promising direction for higher accuracy. This work, carried out as Major Project Phase 2 in the Department of Computer Science & Engineering, MRIT, Mandya, builds a system that runs both approaches on the same infrared image and fuses their outputs into one decision.

The motivation for this work is twofold. First, a faster and more objective assessment reduces the delay between the arrival of a satellite image and a usable warning.

Second, relying on two different ways of reading the same image makes the final decision less sensitive to the weakness of any single method. The system therefore aims to give the user not just a class label, but also the confidence of each branch and of the fused result, so that the output can be judged and not just accepted.

The rest of the paper is organized as follows. Sections II and III state the problem and the objectives. Section IV reviews related work. Sections V and VI describe the methodology and the system architecture, Sections VII and VIII list the tools and implementation modules, Section IX presents the results, and Section X concludes the paper.

Structure of a Tropical Cyclone

Three features of a cyclone matter most for intensity estimation. The **eye** is the roughly circular centre of the storm, where the sky is comparatively clear. The **eyewall** is the ring

of dense clouds that surrounds the eye, and is where the strongest winds of the storm are found. The **spiral rainbands** are curved bands of cloud and rain that wind around the centre. As a cyclone strengthens, these features usually become more organized and easier to recognize in an infrared image, which is why the appearance of the cloud structure carries information about intensity.

The Dvorak Technique

The Dvorak technique estimates cyclone intensity by matching the cloud patterns seen in satellite images against a set of reference patterns. It has been widely used, but it is carried out by an analyst looking at each image, which makes it manual and subjective. The proposed system aims to reduce this dependency by performing the interpretation automatically.

II. PROBLEM STATEMENT

Tropical cyclones are dangerous because they produce extreme winds, heavy rainfall with flooding, and damaging storm surge that can cause inundation of low-lying coastal areas. The key difficulties in assessing them are:

- Manual and subjective methods such as the traditional Dvorak technique are slow and depend on the analyst's judgement.
- A CNN-based model can estimate TC intensity from infrared satellite images, but a single model may not be equally reliable for every storm.
- Image processing can classify a TC from its cloud structure and eye pattern, but on its own it may miss patterns that a learned model captures.
- Combining the two for higher accuracy is a potential area of research, and a system is needed that returns one reliable classification instead of two separate opinions.

III. OBJECTIVES

- Estimate TC intensity (High / Medium / Low) using a CNN-based deep learning model on infrared satellite images.
- Classify TC severity (Severe / Moderate / Normal) using image processing on cloud structure and eye pattern.
- Fuse both approaches into a single decision, improving accuracy and reliability over either method alone.
- Reduce dependency on manual, subjective methods such as the traditional Dvorak technique.
- Support early and accurate classification so that disaster management authorities can warn coastal regions in time.

IV. LITERATURE REVIEW

Recent studies on deep-learning-based cyclone intensity estimation were reviewed before designing the proposed system. Table 1 summarizes four representative works, with the key contribution and the main limitation of each.

Zhang et al. bring cyclone physics into a multi-task network trained on satellite images, which helps intensity prediction but is less effective for extreme cyclones. Manju et al. combine a CNN with ConvLSTM so that the model can use how a storm changes over time, at the cost of requiring sequential images. Tan et al. use a Swin-Unet-based design that recognizes storm morphology, but it needs large amounts of data and high computing power. Tian et al. use a dual-branch attention convolutional network over space and time, which improves prediction but again needs time-series data and more computation.

Table 1: Literature Review Summary

Year	Author	Method	Key Contribution	Limitation
2026	Zhang et al.	Physics-Guided Network	Uses satellite images and cyclone physics to improve intensity prediction.	Less effective for extreme cyclones.
2025	Manju et al.	CNN + ConvLSTM	Uses satellite images and time information for intensity estimation and classification.	Needs sequential images.
2025	Tan et al.	Swin-Unet	Uses storm shape and deep learning for intensity estimation.	Needs large data and high computing power.
2024	Tian et al.	Attention CNN	Uses spatial and time information to improve cyclone intensity prediction.	Needs time-series data and more computation.

Two observations follow from this survey. First, most of the reviewed models gain accuracy by adding temporal information or by using larger and more complex networks, which raises data and computing requirements. Second, none of the reviewed works pairs a CNN with a separate image-processing classifier of cloud structure and eye pattern. The proposed system is motivated by this gap: it works on infrared images and combines a CNN branch with an image-processing branch through a fusion layer.

Compared with the manual Dvorak technique, all four reviewed works are automated, which is an advantage. Their limitations show, however, that better accuracy usually comes at a price: more input data, more images per storm, or more computation. The present project accepts a simpler input — a single infrared image — and tries to obtain the gain in reliability from the fusion of two different views of that image instead.

V. PROPOSED METHODOLOGY

The proposed system follows a five-step methodology, moving from raw infrared satellite images to a single, fused intensity classification. Infrared satellite images are fed into two parallel branches: a CNN model estimates intensity (High / Medium / Low), and an image-processing pipeline classifies severity (Severe / Moderate / Normal) from cloud structure. Both outputs are then combined by a fusion layer to produce one final, higher-confidence class.

Cyclone Classification and Intensity Estimation Workflow

1. **Acquire and Preprocess Images:** INSAT-3D infrared cyclone imagery is loaded and each image is prepared for both branches through storm-centered cropping and normalization. The dataset is then divided into training and testing sets.
2. **Run the CNN Branch:** A convolutional neural network, trained on the preprocessed infrared images, predicts the intensity of the cyclone as High, Medium or Low together with a confidence for each class.
3. **Run the Image-Processing Branch:** The image is preprocessed, relevant visual features are extracted, and the cyclone is classified as Normal, Moderate or Severe based on cloud structure and eye pattern.
4. **Apply the Fusion Layer:** The outputs of the two branches are collected and combined by weighted voting, or by a stacked meta-classifier, into one final intensity class.
5. **Evaluate and Display:** Accuracy, precision, recall and F1-score are computed, and the individual and fused results are displayed to the user.

A. Fusion Strategy

The two branches look at the same storm in different ways, so their errors tend to differ. The fusion layer exploits this. In weighted voting, the class probabilities of each branch are multiplied by a weight and added, and the class with the highest combined score becomes the final class:

$$P(c) = w_1 \cdot P_1(c) + w_2 \cdot P_2(c) \quad (1)$$

spiral rainbands appear in a consistent position for both branches. Normalization then brings pixel values to a common scale, which helps the CNN train in a stable way and makes the image-processing steps behave the same on every image. Finally, the images are divided into training and testing sets, so that every reported metric is measured on images that the CNN did not see while learning.

B. Evaluation Metrics

Each of the three outputs — the CNN, the image-processing model and the fused result — is evaluated on the test set using accuracy, precision, recall and F1-score, defined from the counts of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN):

$$\begin{aligned} \text{Accuracy} &= (TP + TN) / (TP + TN + FP + FN) \\ \text{Precision} &= TP / (TP + FP), \text{ Recall} = TP / (TP + FN) \\ \text{F1-score} &= 2 \cdot \text{Precision} \cdot \text{Recall} / (\text{Precision} + \text{Recall}) \end{aligned}$$

Per-class results are also visualized as confusion matrices, which show which intensity classes the models confuse most often.

C. Data Preparation

The imagery used by the system is INSAT-3D infrared imagery of cyclones. Raw satellite scenes cover a large area, of which only a small part is the storm itself. Storm-centered cropping therefore places the cyclone at the centre of every image, so that the eye, eyewall and result is reported as the corresponding final intensity class, for example Severe giving High. The final class is the level with the highest combined score under Eq. (1).

D. Complementary Roles of the Two Branches

The CNN branch learns its features from data, so it can pick up patterns that are difficult to describe by hand. The image-processing branch works directly on cloud structure and eye pattern, which are the same visual cues that a human analyst looks at, so its reasoning is easier to explain. The CNN gives the intensity output (High / Medium / Low) and the image-processing branch gives the severity output (Severe / Moderate / Normal). Placing them side by side lets the system use the learned and the rule-based view of the same storm.

E. Classes and Decision Mapping

The CNN branch reports intensity as **High**, **Medium** or **Low**, and the image-processing branch reports severity as **Severe**, **Moderate** or **Normal**. These are three-level scales of

the same underlying property, the strength of the storm, so the two outputs can be fused level by level. In

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the prototype, both branches report their probabilities over the levels Normal, Moderate and Severe, and the fused by the image-processing and CNN branches, and w_{ip} and w_{cnn} are their weights, with $w_{ip} + w_{cnn} = 1$. In the demonstration prototype the weights are 65% for image processing and 35% for the CNN. As an alternative to fixed weights, a stacked meta-classifier built with scikit-learn can learn from the outputs of both branches how much each should be trusted.

VI. SYSTEM ARCHITECTURE

The architecture of the system is shown in Fig. 1. The input is an infrared satellite image of a cyclone. The image is sent to two parallel branches. In the CNN branch (2A), a convolutional network estimates intensity and produces an intensity output of High, Medium or Low. In the image-processing branch (2B), a pipeline analyses cloud structure and eye pattern and produces a severity output of Severe, Moderate or Normal.

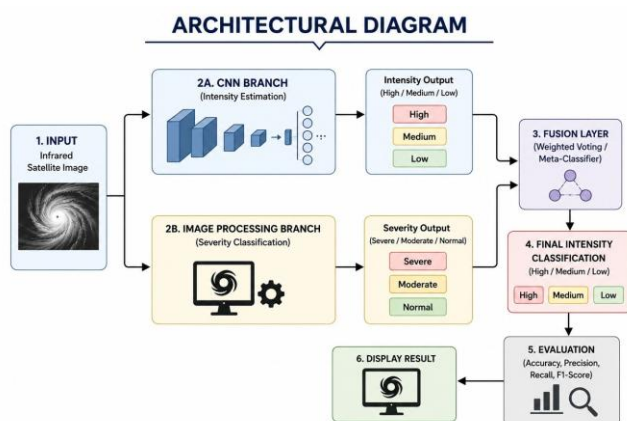


Fig. 1: Architecture of the Proposed System

Both outputs feed the fusion layer (3), which uses weighted voting or a meta-classifier to produce the final intensity classification (4) of High, Medium or Low. The final

class is then evaluated using accuracy, precision, recall and F1-score (5), and the result is displayed to the user (6).

I. Flowchart / Algorithm

The processing steps are given in Fig. 2. The image is first preprocessed (step 2) and then passed to the two branches (steps 3 and 4). The branch outputs are collected (step 5) and combined by the weighted-voting fusion layer (step 6) to compute the final intensity class (step 7). The system then evaluates accuracy, precision, recall and F1 (step 8) and displays the result (step 9).

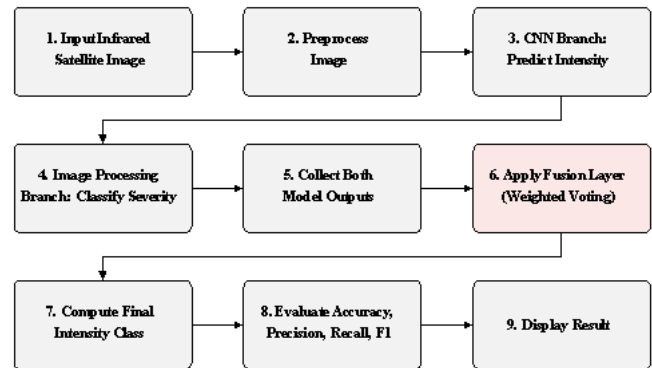


Fig. 2: Flowchart of the Classification Algorithm

Algorithm

Input : infrared satellite image I Output: final intensity class, metrics

1. $I' \leftarrow \text{Preprocess}(I)$ (crop, normalize)
2. $P_{cnn} \leftarrow \text{CNN}(I')$
3. $P_{ip} \leftarrow \text{ImageProcessing}(I')$
4. $P_{fin} \leftarrow w_{ip} * P_{ip} + w_{cnn} * P_{cnn}$
5. $class \leftarrow \text{argmax}(P_{fin})$
6. Evaluate accuracy, precision, recall, F1
7. Display P_{ip} , P_{cnn} , P_{fin} and class

Keeping the two branches independent until the fusion step means that either one can be retrained or improved without changing the other, and that the fusion weights can be tuned separately.

VII. TOOLS AND TECHNOLOGIES

The system is built in Python. Table 2 lists the technologies used and the purpose of each.

Table 2: Tools and Technologies

Technology	Purpose
Python	Core programming language for the entire pipeline
TensorFlow / Keras	Building and training the CNN intensity-estimation model
OpenCV	Image processing
NumPy / Pandas	Numerical computation and dataset handling
Matplotlib / Seaborn	Visualizing training curves and evaluation results
scikit-learn	Fusion layer – meta-classifier and evaluation metrics

VIII. IMPLEMENTATION (MODULES)

The system is divided into six modules, each with a single responsibility.

- **Data Loading & Preprocessing:** Loads INSAT-3D infrared cyclone imagery, performs storm-centered cropping, normalization and the train / test split.
- **CNN Intensity Estimation:** Trains a convolutional neural network that estimates TC intensity (High / Medium / Low) from preprocessed infrared images.
- **Image Processing Classification:** Preprocesses infrared satellite images, extracts relevant visual features, and classifies cyclone severity as Normal, Moderate, or Severe.
- **Fusion:** Combines the CNN and image-processing outputs via weighted voting / a stacked meta-classifier into one final intensity class.
- **Evaluation:** Computes accuracy, precision, recall and F1-score for the CNN, the image-processing model, and the fused output.
- **Results & Visualization:** Visualizes predictions, confusion matrices and per-class performance for the final report.

The inputs and outputs of the modules are summarized in Table 3.

Table 3: Inputs and Outputs of the Modules

Module	Input	Output
Data Loading & Preprocessing	INSAT-3D infrared images	Cropped, normalized train / test sets
CNN Intensity Estimation	Preprocessed images	High / Medium / Low with confidence
Image Processing Classification	Preprocessed images	Normal / Moderate / Severe with confidence
Fusion	Outputs of both branches	One final intensity class
Evaluation	Predictions and true labels	Accuracy, precision, recall, F1
Results & Visualization	Predictions and metrics	Result display, confusion matrices

User Interface

A web interface wraps the pipeline so that it can be used without touching the code. The user uploads an infrared satellite image in JPG, PNG, TIF or TIFF format and presses the Analyze Cyclone button. The page then shows the uploaded image, the image-processing result, the CNN result and the fused final result, each with its confidence. The page also carries a note that this is a student research prototype and that its output should be validated with real meteorological data before any scientific conclusions are drawn.

IX. RESULTS

The prototype was tested by uploading an infrared cyclone image through the web interface. The upload page is shown in Fig. 3(a). After analysis, the page reports the output of each branch and the fused decision, as shown in

Fig. 3(b) to 3(d).

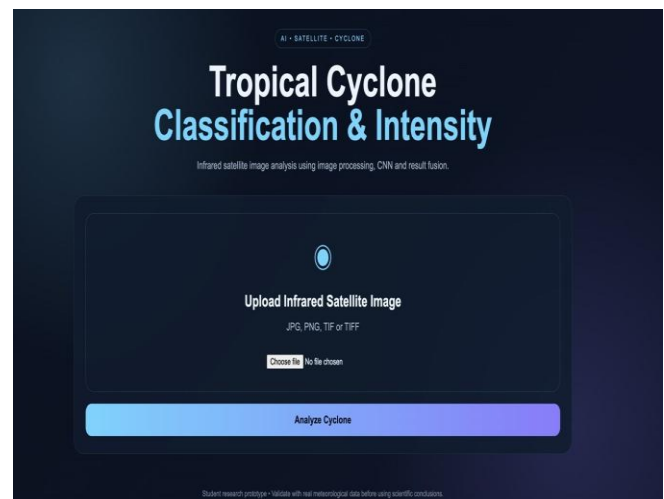


Fig. 3(a): Upload Page of the Web Interface

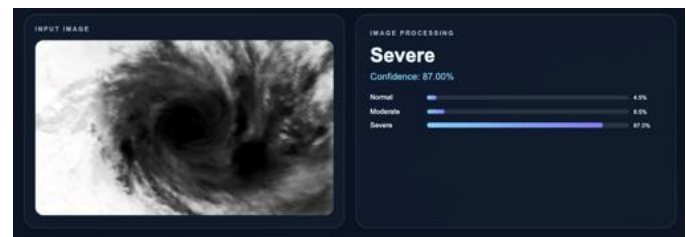


Fig. 3(b): Image-Processing Result



Fig. 3(c): CNN Intensity Result

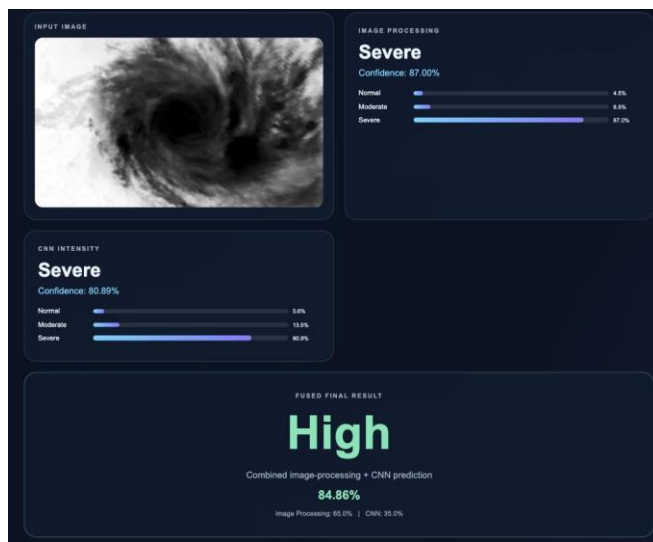


Fig. 3(d): Combined Output with Fused Final Result

The class probabilities for this sample are given in Table 4.

Table 4: Output for the Sample Infrared Image

Branch	Normal	Moderate	Severe	Output	Confidence
Image processing	4.5%	8.5%	87.0%	Severe	87.00%
CNN	5.6%	13.5%	80.9%	Severe	80.89%
Fused (65 : 35)	—	—	—	High	84.86%

A. Walk-through of the Sample

The sample is processed in four stages. (1) The infrared image is uploaded and shown in the input panel. (2)

The image-processing branch analyses the cloud structure and eye pattern and returns a probability for each level, with Severe clearly highest. (3) The CNN branch independently returns its own probabilities, again with Severe highest. (4) The fusion layer combines the two with the 65 : 35 weights and shows the final class and its confidence in the combined panel.

B. Discussion

Both branches classified the storm as Severe: the image-processing branch with a confidence of 87.00% and the CNN branch with 80.89%. The fusion layer combined them with weights of 65% and 35%, giving a final confidence of $0.65 \times 87.00 + 0.35 \times 80.89 \approx 84.86\%$, and reported the final intensity class as High. Because the weights favour the image-processing branch, the fused confidence lies between the two individual confidences and closer to that of image processing.

In this sample the two branches agree, so the fused result simply confirms them with a single confidence value. The value of the fusion layer is greatest when the branches disagree, since the weighted combination then settles on the class that is better supported overall. The accuracy, precision, recall and F1-score of the CNN, the image-processing model and the fused output over the full test set are computed by the evaluation module described in Section VIII.

Advantages of the Proposed System

- **Automation:** The classification runs without manual interpretation of cloud patterns, reducing dependency on subjective methods such as the Dvorak technique.
- **Higher reliability:** Fusing a CNN with an image-processing classifier improves accuracy and reliability over either method alone, and a disagreement between branches is visible to the user.
- **Modularity:** Each stage — preprocessing, CNN, image processing, fusion and evaluation — is a separate module that can be improved independently.
- **Ease of use:** The web interface needs only an uploaded infrared image and one button press, and shows the confidence of each branch and of the final result.

Applications

- Early and accurate classification of cyclones to help disaster management authorities warn coastal regions in time.
- A second, objective opinion for analysts who currently assess cyclone intensity by hand.

- Academic study of how image-processing and deep-learning methods can be combined for satellite image analysis.

Limitations

The present system is a student research prototype. It classifies a storm into three coarse levels from a single infrared image, so it does not use the way a storm changes over time. The fusion weights in the prototype are fixed at 65% and 35%, and, as the interface itself notes, the results should be validated with real meteorological data before they are used for scientific conclusions.

X. CONCLUSION

This paper presented a system for tropical cyclone classification and intensity estimation that combines a CNN with an image-processing pipeline. The CNN estimates intensity from infrared satellite images, the image-processing branch classifies severity from cloud structure and eye pattern, and a fusion layer merges both into one final class. Compared with manual, subjective methods such as the Dvorak technique, the system gives an automated and repeatable assessment, and the web interface makes it simple to use. The sample result shows both branches and the fused decision with their confidence scores.

The main contribution of the work is the way in which the two approaches are put together. Each branch has its own output and confidence, and the fusion layer turns them into a single decision, so the user sees both the individual opinions and the combined result. The modular design allows the CNN, the image-processing pipeline and the fusion strategy to be refined separately in later work.

Future work may extend the system to larger and more varied cyclone datasets, add sequences of images so that the change of a storm over time can be used, tune or learn the fusion weights automatically, and test the system on live satellite feeds so that it can support disaster management authorities in warning coastal regions in time.

XI. ACKNOWLEDGMENT

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