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Cyclone Nature Prediction with the help of a Customized SVM Model

Md. Jakir Hossen*, Fariya Sultana Prity, Rasel Ahmed and Md. Sharifuzzaman

***Abstract* – Efficiently predicting the nature of tropical cyclones through machine learning techniques has always posed a challenge in the quest to save human lives. While existing research has proposed various methods to accurately predict cyclone behavior and reduce its impact on humanity, this paper introduces a unique customized Support Vector Machine (SVM) model. Unlike existing models, this machine learning-based custom model enhances evaluation metrics, offering significant improvements in binary classification forecasting. The paper also presents a schematic diagram outlining an architectural design for cyclone nature detection utilizing satellite images. The proposed customized SVM model achieves impressive classification metrics, with accuracy at 95%, precision at 94.78%, recall at 94.5%, and an F1-score of 94.9%. In contrast, other models such as Random Forest (RF), SVM, decision tree (DT), and Logistic Regression (LR) fall short, failing to reach an accuracy exceeding 92%. Furthermore, future work may involve the development of hybrid models.**

Keywords—Cyclone Nature, Deep Learning, Customized SVM, Accuracy, Prediction.

I. Introduction

Predicting the characteristics of tropical cyclones, including factors like their strength, path, and sudden intensification, remains a critical task within the field of meteorology and disaster management. It involves gaining insight into the intricate dynamics of these formidable storms to offer timely and precise forecasts. This, in turn, empowers communities to brace themselves for potential consequences, thereby reducing risks to human lives and property. Nonetheless, this endeavor is marked by substantial difficulties due to cyclones' inherent intricacy and variability [1].

A fundamental concern in cyclone forecasting is the imperative for enhanced precision and lead time in predictions. Traditional forecasting techniques, while valuable, often struggle to capture the intricate and swiftly changing nature of cyclones. This is where deep learning, a subset of machine learning, comes into play. Deep learning algorithms, particularly neural networks with multiple layers, have displayed remarkable aptitude in processing extensive and intricate datasets, rendering them well-suited for addressing the challenges linked with cyclone prediction [2,3].

By leveraging deep learning techniques, researchers aim to enhance our understanding of cyclone behavior and improve forecasting accuracy. These approaches involve training neural networks on vast amounts of historical meteorological data, including satellite imagery, atmospheric measurements, and environmental variables. Deep learning models can then learn intricate patterns and relationships within this data, enabling them to make

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more precise predictions about cyclone characteristics.

The proposed system enhances the accuracy of cyclone's nature to predict earlier to take precautions before it becomes a threat to human lives. The paper's notable contributions include the following:

- A distinct way to enrich the prediction of cyclone nature is through a custom SVM model for binary classification.
- Impressive experimental results were achieved in this study. The authors conducted a rigorous investigation and validation of the performance pattern, focusing on a specific parameter known as RBF (Radial Basis Function). To ensure the reliability of the data, each workload was performed at least five times.

The paper is organized in the following manner: The introduction provides an overview of the research problem, highlighting its significance and connecting it to existing literature. In the literature review section, we comprehensively explore prior research and establish the conceptual framework. The methodology section elucidates the adopted research approach and details the data collection and analysis techniques. Subsequently, the Results and Analysis section presents the research findings in alignment with the re-search objectives and the conceptual framework, offering insights to address the research question. Finally, the Conclusion section synthesizes the research aim and major findings, providing a comprehensive closure to the study.

II. Literature Review

Several studies propose integrating satellite images of tropical cyclone convection with traditional environmental predictors using deep learning models. For instance, one study utilized 20 deep-learning models and ensemble approaches to predict Vmax at +24h. This ensemble approach yielded more convenient Vmax distribution pre-dictions compared to individual models. The authors also compared their technique to functional forecasts and achieved better rapid intensification detection probabilities. Future work in this area includes further model combinations for improved prediction accuracy [1]. Another set of studies focused on systematically extracting tropical cyclone information using deep learning frameworks. These frameworks offer applications in intensity and wind radius estimation. However, using satellite images with various sensors may introduce uncertainty in data. Furthermore, some researchers suggest a need for feedback mechanisms to enhance model knowledge in tropical cyclone research [2]. One study proposed a C-LSTM model based on data from 1949 to 2021 for typhoon path prediction. Comparing this model with LSTM, the authors demonstrated fewer errors with the C-LSTM approach. Future work involves optimization and extracting information from diverse data sources, including image, numerical, and observed data [3].

Additionally, A solution where modified the CCT model with a different approach to analyze satellite images of flooded areas. This model achieved 98.79% accuracy with reduced computational requirements. They also incorporated an AI framework called LIME for interpretable predictions [4]. Researchers proposed a novel data-driven model combining spatial location and meteorological features to predict cyclone tracks. Their model outperformed traditional methods and various deep learning (DL) architectures, including CNN, CNN-RNN, CNN-GRU, RNN, GRU, and AE-RNN. Future work includes comparing the model with the latest numeric and statistical methods and improving performance for multiple cyclones [5]. A unique framework was introduced to predict cyclone formation by integrating a trigger function along with a deep predictive model based on CNN. The model achieved a 95% detection probability with a 21.69% false alarm ratio. Future research may focus on further optimization and data integration [6]. Researchers proposed ConvLSTM to efficiently extract spatial and temporal information for adverse weather events in India. They validated the model's performance using image data and additional metrics. Future work may explore advanced techniques and data sources [7]. They suggested using YOLO for detecting and locating cyclones and R-CNN for predicting storm locations. They compared various interpolation techniques to enhance deep learning algorithms' performance and recommended densified datasets for further improvement [8]. A framework was proposed for processing radiance data using YOLOv3 for cyclone detection. The authors discussed the potential extension to other models and emphasized optimization through fine-tuning hyperparameters [9]. Three deep learning models were developed for tropical cyclone trajectory prediction, with the data-driven MLP-LSTM model outperforming MLP and LSTM. The authors highlighted the importance of flexible topologies [10].

Another solution where introduced a system for cyclone pre-diction from satellite images and developed an object detection method through deep learning to detect cyclone eyes. Their approach outperformed conventional techniques. Future work could involve hybrid models [11]. A study compared six deep-learning models for identifying the center location of tropical cyclones. YOLOv4 achieved the highest accuracy at 99.84% and demonstrated the ability to detect multiple cyclone locations [12]. An ensemble technique was introduced to locate tropical cyclone centers and classify them using machine learning models. The authors emphasized the model's generalization ability and its potential to detect lower cyclone categories [13]. Researchers addressed the challenges of detecting cyclone patterns through optical flow estimation and also deep learning models. Their proposed technique improved accuracy compared to traditional methods [14]. Studies analyzed remote sensing data, including precipitation and wind satellite data, to detect cyclones using CNN models. The minimum accuracy achieved for cyclone vortex detection was 90% [15]. The authors proposed integrating numerical precipitation estimation with CNN models to analyze image data and estimate precipitation. The study aimed to enhance prediction accuracy through data-driven methods [16]. A deep learning model was proposed to detect tropical cyclone presence in satellite images based on CNN. The model accomplished an average of 99% accuracy with a smaller parameter count. The authors suggested that this model fulfills the objective of cyclone detection [17]. A neural network model was developed by the researchers where trajectory data and atmospheric images were integrated to provide real-time updates on new storms. Their method demonstrated superior performance compared to conventional forecasting methods [18]. A deep CNN model was presented for estimating cyclone intensity, outperforming existing methods based on accuracy and error metrics. The authors suggested future work with different network architectures and parameters [19]. Finally, a multistage deep learning framework was proposed for cyclone detection, achieving high precision, specificity, and accuracy in testing satellite images. The authors used Bayesian optimization for hyperparameter tuning [20].

One another solution used deep learning techniques, specifically convolutional neural networks (CNNs), for predicting tropical cyclone (TC) formation. They tested two CNN architectures, ResNet and UNet, using historical weather data. ResNet and UNet both show promising results in predicting TC formation within 12-18 hours using environmental data from the Pacific Ocean. However, ResNet generally outperforms UNet across accuracy metrics. The study finds that a larger input domain leads to better predictions, suggesting that CNNs can capture essential far-field information. They introduces a significant shift from traditional TC prediction methods, leveraging deep learning to provide early warnings about cyclone formations effectively [21].

Moreover, this solution used a new system for predicting tropical cyclone tracks with uncertainty using machine learning within a conformal prediction framework. They evaluates ten major machine learning models and conformal forecasting methods, focusing on their ability to forecast paths with uncertainty over 6, 12, and 24-hour periods. The model effectively generates reliable forecast regions, aiding decision-makers in preparing for potential hazards. The results show that machine learning can predict tropical cyclone tracks with high accuracy and tight uncertainty intervals, highlighting its potential for future use in tropical cyclone forecasting and risk communication [22].

These papers collectively demonstrate the potential of deep learning models for predicting various aspects of tropical cyclones, including intensity, location, and formation. While these studies have made significant advancements, they also highlight the need for further research in optimizing models, handling data limitations, and exploring hybrid approaches. Advanced deep learning techniques offer promising prospects for improving cyclone prediction accuracy and reducing the impact of these destructive natural events.

III. Methods

A. Proposed Method

The proposed method of this study. For this study satellite and meteorological data are used as input data. Data were pre-processed based on the nature of the dataset. Feature Extraction and selection depend on the feature importance of the model. Cyclone nature detection algorithms help to predict the location of cyclone nature early and more accurately. Validation of the data shows the reliability of the model. Alerting and reporting system helps to be aware of the upcoming cyclone and also visualizing prediction results making it more interactive for the user of this system. However, archiving and monitoring continuously of the system is really important to maintain and predicting the cyclone location or nature through forecasting.

B. Dataset Description

The NHC releases the historical database for tropical cyclones in a pattern referred to as HURDAT, which is also known as Hurricane Database. These databases, namely Atlantic HURDAT2 and NE/NC Pacific HURDAT2, provide six-hourly data regarding the position, maximum wind speeds, central pressure, and, from 2004 onwards, the size of documented tropical cyclones and subtropical cyclones [23].

C. Dataset Pre-processing

Data.isna().sum()) is used to remove the null value. So, no specific imputation or removal of missing data is performed.

D. Feature Engineering

The Latitude and Longitude columns are processed to create new binary categorical columns: Latitude_Hemisphere and Longi-tude_Hemisphere. These columns indicate whether the latitude is in the Northern Hemisphere (0 for N, 1 for S) and whether the longitude is in the Eastern Hemisphere (0 for E, 1 for W). The Latitude and Longitude columns are further cleaned by extracting only the numeric part of the coordinates. The 'Date' column is converted to a datetime format, and two new columns, 'Month' and 'Year', are derived from it.

E. Training Dataset

Most charts graphs and tables are one column wide (3 1/2 inches or 21 picas) or two-column width (7 1/16 inches, 43 picas wide). We recommend that you avoid sizing figures less than one column wide, as extreme enlargements may distort your images and result in poor reproduction. Therefore, it is better if the image is slightly larger, as a minor reduction in size should not have an adverse effect on the quality of the image.

F. Random Forest Classifier

Random Forest operates by creating an ensemble of decision trees, where each tree is constructed from a random subset of the training data and a random subset of the features. This randomness helps reduce overfitting, improve generalization, and enhance the model's performance. The final prediction in a

Random Forest is typically made by aggregating the predictions of all individual trees, often through majority voting for classification tasks or averaging for regression tasks. This ensemble approach provides a more stable and accurate prediction than any single decision tree. One of the fundamental equations used in the Random Forest algorithm is the splitting criterion for decision trees within the ensemble. This criterion helps determine how the data should be divided at each node of the tree. One common criterion is Gini impurity, represented by the following equation:

$$Gini\ Index = 1 - \sum_{i=1}^{n}(P_i)^2 \quad (1)$$

Here,

Gini Index represents the Gini impurity for a particular node.

n is the number of classes in the target variable.

pi is the proportion of instances belonging to class i in the node.

The Gini impurity is used to assess how often a randomly chosen element from the dataset would be incorrectly classified based on the distribution of class labels at that node. Decision trees in Random Forest use this criterion to make splits that maximize the reduction in impurity, leading to effective and accurate predictions [24].

G. Support Vector Machine (SVM) Classifier

Support Vector Machine (SVM) is a powerful and widely used machine learning classifier that has gained prominence due to its ability to perform well in both linear and non-linear classification tasks. SVM aims to find the optimal hyperplane that best separates data points belonging to different classes in a high-dimensional feature space. This hyperplane is chosen to maximize the margin, which is the distance between the hyper-plane and the nearest data points from each class.

The SVM classifier can be mathematically defined as follows:

Given a set of training data points (x_i, y_i), where x_i represents the feature vector of the ith data point, and y_i represents the class label (either +1 or -1), the objective of the SVM is to find a hyper-plane defined by the equation:

$$w \cdot x + b = 0 \quad (2)$$

where 'w' is the weight vector perpendicular to the hyperplane, 'x' is the feature vector, and 'b' is the bias term.

The SVM classifier assigns data points to one of two classes based on the sign of the equation w·x + b. If w·x + b > 0, the data point is classified as class +1; if w·x + b < 0, it is classified as class -1 [24,25].

H. Logistic Regression

Logistic Regression is a statistical modeling technique utilized in binary classification scenarios, where the dependent variable has two categorical levels, typically represented as 0 and 1. This method finds applications across a range of disciplines such as medicine, finance, and machine learning due to its straightforwardness and ease of interpretation. At its core, logistic regression revolves around the logistic function (commonly known as the sigmoid function), which quantifies the likelihood of an input being classified into the positive class (often designated as 1).

The logistic function is defined as:

$$P(Y = 1|X) = \frac{1}{1+e^{-\beta T X}} \quad (3)$$

P(Y=1|X) represents the probability that the outcome variable Y is equal to 1 given the input features X.

- β is a vector of coefficients that determine the relationship between the input features and the log-odds of the positive class.
- X represents a collection of input features.

The logistic function converts a linear combination of the input features βTX into a value within the range of 0 to 1. The output can be interpreted as the probability of the positive class [24][25][26][27].

I. Decision Tree

The Decision Tree algorithm is represented by a tree structure where each internal node represents a decision based on a specific feature, and each leaf node represents a class label (in classification) or a numeric value (in regression). The goal of a Decision Tree is to create a model that can make accurate predictions or classifications by branching through the tree based on the feature values of the input data. The core equation used in Decision Trees is the splitting criterion, which determines how the tree decides to split the data at each node [26][28]. One of the commonly used equations for this purpose is the Gini impurity for classification problems:

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$$Gini(D) = 1 - \sum_{i=1}^{c}(p_i)^2 \quad (4)$$

Where:

- Gini(D) is the Gini impurity for dataset D.
- c is the number of classes in the dataset.
- pi is the probability of selecting a sample with class i at random.

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J. Accuracy

Accuracy is a fundamental metric used in various fields to evaluate the performance of a predictive model or measurement system. It quantifies the degree to which the model's predictions or measurements align with the true or observed values. In the context of classification tasks, accuracy quantifies the ratio of accurately classified instances among the total instances considered.
Mathematically, accuracy (Acc) is defined as:

$$Accuracy\ (Acc) = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Prediction} \qquad (5)$$

"Number of Accurate Predictions" indicates how many times the model's predictions align with the actual or observed values.
"Total Number of Predictions" refers to the cumulative count of predictions generated by the model.
Accuracy is generally presented as a percentage, spanning from 0% (reflecting no accurate predictions) to 100% (indicating flawless predictions) [31-34].

K. Precision

Precision is a key metric in the field of statistics and machine learning, widely employed to evaluate the effectiveness of a classification or prediction model. It measures a model's capability to accurately recognize positive instances among the total instances it designates as positive. Precision holds significant importance in situations where inaccuracies in identifying positives can be expensive or undesirable, like in medical diagnoses or fraud detection.
Precision is calculated using the following equation:

$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Positive\ (FP)} \qquad (6)$$

In this equation:
True Positives (TP) are a measure of correctly predicted positive instances.
False Positives (FP) refer to instances predicted as positive but are negative. Precision is typically quantified on a scale from 0 to 1, with greater values suggesting improved precision.
A precision score of 1 signifies that all positive predictions from the model are accurate, while a score of 0 implies that none of the positive predictions are accurate [35].

L. F1-Score

The F1-Score, also referred to as the F-Measure, serves as a widely employed metric in machine learning and information retrieval to assess the effectiveness of binary classification models. It amalgamates precision and recall into a unified measure, proving especially valuable in scenarios involving imbalanced datasets where one class substantially dominates the other.
The F1-Score is defined as the harmonic mean of precision (P) and recall (R):

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \qquad (7)$$

where:
Precision (P) is a metric that evaluates the accuracy of positive predictions by assessing the ratio of true positive predictions to the total number of positive predictions.
Recall (R), also referred to as sensitivity or the true positive rate, measures the model's capacity to capture all actual positive instances within the dataset. It is calculated as the ratio of true positive predictions to the total number of actual positive instances.

The F1-Score is a metric that falls within the range of 0 to 1, where larger values indicate superior model performance. In a binary classification scenario, a flawless model achieves an F1-Score of 1, while a completely random model achieves an F1-Score of 0.5 [36,37].

IV. Results and Discussion

This section shows the results of the used models evaluation metrics.

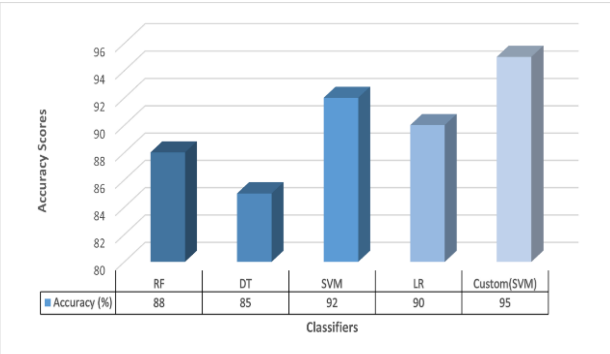

FIGURE 1. Accuracy of all proposed classifiers.

Figure 1 shows the situation as a thorough analysis of the performance of several classifiers is shown. The matching acronym for each classifier, such as RF (Random Forest), DT (Decision Tree), SVM (Support Vector Machine), LR (Logistic Regression), and a particular SVM model, serves as a representation. The accuracy rates of these classifiers have undergone painstaking calculation and extensive testing. With a remarkable accuracy rate of 92%, the SVM classifier shines out, closely followed by RF and DT with accuracy rates of 88% and 85%, respectively. With a 90% accuracy rate, LR performs admirably as well. The best model, nevertheless, is the customized SVM one, which has a remarkable accuracy rate of 95%. These outcomes demonstrate the custom SVM model's efficiency in contrast to other classifiers.

Figure 2 shows a thorough comparison of the accuracy ratings for the several suggested classifiers. Decision Trees (DT) closely follows with a precision rate of 84.61%, while Random Forest (RF) has a precision rate of 88.2%. With an accuracy score of 91.2%, Support Vector Machine (SVM) stands out as a top performer. Additionally, Logistic Regression (LR) performs well, reaching an accuracy rate of 89.32%.

Notably, the individualized SVM classifier, or "custom (SVM)," outperforms all others with a remarkable precision rate of 94.78%. This visual depiction provides a clear picture of the accuracy performance of the classifiers, with the custom SVM classifier outperforming the others.

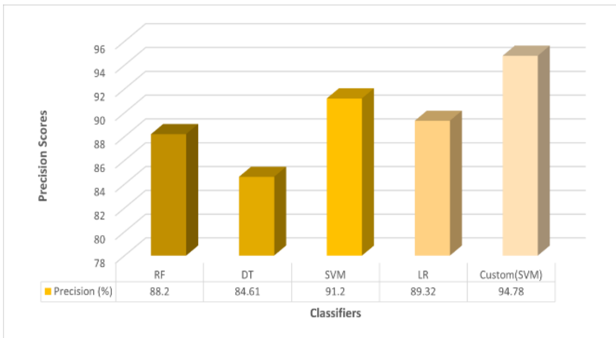

FIGURE 2. Precision of all proposed classifiers.

FIGURE 3. Recall of all proposed classifiers.

Figure 3 provides a good demonstration of how well various classifiers perform in terms of recall. It demonstrates how well each classifier can find advantageous occurrences in the dataset. Decision Trees (DT) come in second place with a recall rate of 85.61%, closely followed by Random Forest (RF) with 87.2%. With a remarkable recall rate of 90%, Support Vector Machine (SVM) shines out, while Logistic Regression (LR) is not far behind at 89.8%. The performance of our customized SVM implementation, which yields an exceptional recall rate of 94.5%, is particularly notable. The effectiveness of our proprietary SVM model in identifying positive cases within the dataset is shown by this visual depiction, which offers a succinct comparison of recall performance among these classifiers.

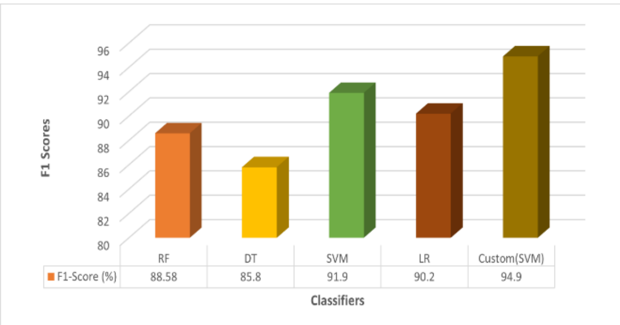

FIGURE 4. F1-Score of all proposed classifiers.

Figure 4 is an illustration of the F1 scores attained by several classifiers. The Random Forest (RF) model among these classifiers receives an F1-Score of 88.58%, closely followed by the Decision Tree (DT) classifier with a score of 85.8%. With an F1-Score of 91.9%, the Support Vector Machine (SVM) stands out as performing well and proving to be useful for classification tasks. The Logistic Regression (LR) model generates a good F1-Score of 90.2% in a similar manner. The best performance, however, is provided by a unique SVM model that exceeds all others with an astounding F1-Score of 94.9%. This comparison demonstrates the custom SVM classifier's advantage in obtaining the greatest F1 score, possibly making it the best option for this classification problem.

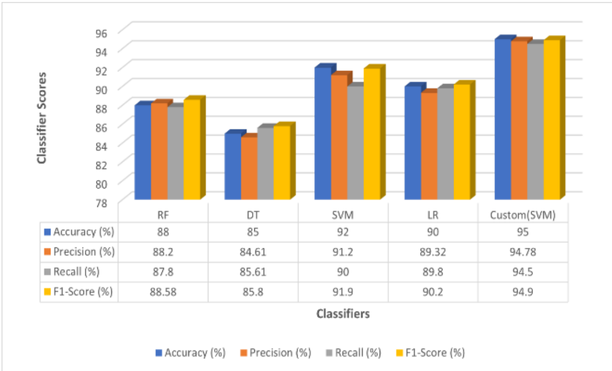

FIGURE 5. Summary of all proposed classifier models.

A thorough list of all the suggested classifier models can be seen in Figure 5, allowing for a quick and meaningful comparison of each model's performance. The chart likely includes metrics such as accuracy, precision, recall, F1-Score, and possibly others, depending on the specific evaluation criteria used. Among these models, it becomes evident that the customized Support Vector Machine (SVM) classifier stands out as the top performer, delivering the most impressive results in terms of classification accuracy and overall predictive power. This visually compelling representation highlights the effectiveness of the customized SVM model in comparison to its counterparts, signifying its superiority in accurately classifying data points within the given context.

TABLE 1. Existing proposal model with accuracy.

Citation	EXISTING PROPOSED MODEL	Accuracy
[8]	Deep Learning	84
[11]	Deep Learning	87
[15]	CNN	90
[19]	CNN	90
[20]	Multistage Deep Learning Framework with R-CNN	86.55

TABLE 2. Proposed model for this study with accuracy, precision, recall, and f1-score

Proposed Model	ACCURACY (%)	Precision (%)
RF	88	88.2
DT	85	84.61
SVM	92	91.2
LR	90	89.32
Customized SVM	95	94.78

In Table 1, we observe that existing deep-learning models have achieved accuracies ranging from 84% to 90%. Notably, Kumawat and Jaiswal (2021) and Pradhan et al. (2017) both attained an accuracy of 90% using Convolutional Neural Net-works (CNN). These results highlight the efficacy of deep learning (DL) techniques in cyclone detection, especially when processing satellite data. Turning our attention to Table 2, which represents the accuracy, precision, recall, and F1-score of the proposed customized SVM model, we notice a substantial improvement. The specially configured SVM model attains an impressive accuracy of 95%, surpassing all the existing deep learning models in Table 1. This outcome underscores the model's capacity to provide highly accurate cy-clone predictions.

Furthermore, the precision, recall, and f1-score of the suggested customized SVM model are also remarkable. With precision at 94.78%, recall at 94.5%, and an F1-score of 94.9%, the model demonstrates a balanced ability to correctly classify cyclones while minimizing false positives and false negatives. These metrics highlight the model's strong performance regarding both accuracy and dependability. Machine learning algorithms should be adapted for applications since the customized SVM model outperformed current deep learning models in terms of accuracy. In this case, cyclone detection specific SVM models outperform common deep learning architectures. This achievement has important ramifications for improving cyclone fore-casting, boosting catastrophe preparedness, and ultimately protecting both human lives and the environment. The findings and subsequent discussion demonstrate how effective the suggested customized SVM model is for cyclone identification, attaining impressive accuracy and a balanced precision-recall performance. This study contributes to the expanding corpus of meteorological information and gives hope for cyclone prediction systems.

V. Conclusion

This study demonstrates the effectiveness of a customized Support Vector Machine (SVM) model in predicting tropical cyclone features, a crucial component of operational weather forecasting. This ground-breaking model plays a crucial part in protecting both the environment and human lives while also enhancing prediction accuracy. A robust framework for recognizing cy-clone features is developed by utilizing satellite images and cloud-based data storage, enabling continual monitoring and study of these dynamic weather events. However, with an accuracy of 95%, precision of 94.78%, recall of 94.5%, and f1-score of 94.9%, the customized SVM model out-performs other conventional models like Random Forest, decision tree, SVM, and Logistic Regression. Future inclusion of a hybrid model might lead to even greater accuracy gains, highlighting the significance of ongoing study and innovation in cyclone prediction for the good of society and the environment.

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Author Contributions

Md. Jakir Hossen: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;

Fariya Sultana Prity: Project Administration, Writing – Review & Editing;

Rasel Ahmed: Project Administration, Supervision, Writing – Review & Editing;

Md. Sharifuzzaman: Project Administration, Supervision, Writing – Review & Editing.

Conflict of Interests

There are no conflicts of interest related to the research, authorship, or publication of this article.

Ethics Statements

Ethical approval was not applicable to this research since it did not involve human participants, animals, or sensitive data.

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