



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 10, October 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.524

9940 572 462

6381 907 438

ijirset@gmail.com

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Forecasting on Typhoons Images by EDGE Histogram and JPEG Coefficients Filter by Deductive Learning

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ABSTRACT: The study presents a comparative analysis of various machine learning classifiers for forecasting typhoons using advanced image filters and modeling techniques. Six different combinations of filters and algorithms were evaluated based on key performance metrics, including accuracy, precision, recall, ROC, PRC, and computational time. The "JPEG Coefficient Filter with Logistic" model demonstrated the highest accuracy at 87.56% and superior precision, recall, ROC, and PRC values, indicating its strong predictive capability in accurately forecasting typhoon behavior. However, this model also had the highest computational time at 2.98 seconds, suggesting a trade-off between prediction accuracy and computational efficiency. In contrast, the "Edge Histogram Filter with Logistic" classifier achieved the lowest accuracy of 76.75%, with relatively moderate precision and recall but demonstrated faster computation at 1.06 seconds. Models such as the "Edge Histogram Filter with SGD" and "JPEG Coefficient Filter with Gaussian Processes" balanced high accuracy and precision with moderate processing times, indicating potential for efficient and accurate forecasting. The findings illustrate that different combinations of feature extraction filters and classifiers yield varying levels of predictive performance and computational demands. This highlights the importance of selecting appropriate models based on specific forecasting requirements, such as prediction accuracy, real-time responsiveness, and resource constraints. Overall, these insights contribute to developing robust and effective typhoon forecasting models by leveraging advanced machine learning techniques to enhance prediction accuracy and timeliness, thereby improving risk assessment and disaster preparedness strategies.

KEYWORDS: Typhoon, Edge Histogram Filter, Logistic, JPEG Coefficient Filter, SGD

I. INTRODUCTION

Typhoon forecasting is a critical aspect of meteorology, aiming to predict the development, path, intensity, and impact of powerful tropical cyclones. Typhoons pose significant threats to coastal and inland communities, often bringing destructive winds, heavy rainfall, and life-threatening storm surges. Traditional forecasting methods rely on data from satellites, weather buoys, radar systems, and atmospheric measurements, processed by sophisticated numerical models. However, recent advances in machine learning have further enhanced forecasting accuracy by leveraging vast datasets to detect patterns and make highly precise predictions. These AI-driven models augment existing methodologies, enabling more accurate and timely forecasts that are vital for effective disaster response and preparedness.

Machine learning techniques have revolutionized typhoon forecasting by enabling faster and more accurate predictions of storm behavior. Deep learning algorithms can analyze historical data, such as past storm trajectories, atmospheric conditions, and ocean temperatures, to identify complex relationships and predict future movements and intensities. Machine learning models are also adept at recognizing non-linear patterns and correlations that traditional models may overlook, providing improved forecasts of rapid changes in a storm's strength or track. For instance, neural networks can analyze satellite imagery in real-time, offering crucial insights into developing weather systems and refining

estimates of a typhoon's size and wind field. This rapid, data-driven approach helps meteorologists make more informed predictions and issue timely warnings to the public.

The integration of machine learning into typhoon forecasting systems has been facilitated by growing computational power and data accessibility. Machine learning models continuously learn and adapt as new data becomes available, improving their predictive accuracy over time. Collaboration among meteorological agencies worldwide has led to the sharing of large datasets that fuel these models and drive innovation in predictive techniques. By complementing traditional numerical models with AI-driven insights, forecasters can provide more accurate, longer-range predictions, thereby enhancing early warning systems and disaster management strategies. As climate change leads to shifts in weather patterns, machine learning remains a key tool in the ongoing quest to better understand and predict the complexities of typhoons and other severe weather events.

This work organizes section 2 has literature survey, section 3 has materials and methods and section 4 has results and discussions and section 5 has conclusions.

II. LITERATURE SURVEY

This work focuses the related works of this research. Typhoons pose a significant threat[1] to human lives and property, making accurate predictions of typhoon behavior crucial for risk mitigation and effective disaster management. Satellite imagery is extensively used in typhoon research due to its comprehensive coverage, timeliness, and ease of acquisition, serving as a critical data source for predicting typhoon cloud patterns. However, existing studies[2] often overlook multi-scale features, resulting in substantial information loss and less detailed, imprecise predictions. To address this gap,[3] we developed an Enhanced Multi-Scale Deep Neural Network (EMSN) to forecast typhoon cloud images three hours in advance. The EMSN comprises two key components: a feature enhancement module and a feature encode-decode module. The model takes eight consecutive input images, utilizing the feature enhancement module to extract relevant features from historical data. To account for varying contributions from images at different time steps, channel attention is employed to highlight important features. The feature encode-decode module leverages ConvLSTMs to capture spatially and temporally correlated information at various scales. Skip connections are also utilized to preserve low-level information and minimize loss during downsampling. Comparative experiments[4] demonstrated the EMSN's superior prediction quality and efficiency in forecasting typhoon cloud images compared to existing models.

Another study focused[5] on a hybrid CNN model that integrates satellite spatial features and numerical prediction outputs to enhance tropical cyclone (TC) intensity forecasts at 24, 48, and 72-hour lead times, significantly outperforming Korea Meteorological Administration (KMA) forecasts. Further advancements[6] include an automated neural network method using Sentinel-2A satellite images and crowdsourced geospatial data for precise urban green space (UGS) mapping, achieving 94.6% classification accuracy through multi-scale feature extraction, multi-modal fusion, and boundary enhancement modules. Additionally, researchers[7] employed an ensemble of DeepLabV3+ sub-models to segment snow in Sentinel-2 data, surpassing traditional spectral indices with mIoU values ranging from 0.8075 to 0.9538. Other contributions include a 1D-CNN model for mapping major and minor algal pigments using hyperspectral data, providing spatial maps of algal biomass and species distribution with R^2 values between 0.71 and 0.87 for key pigments.

In related work, a lightweight CNN model was proposed [8] for efficient forest mapping using Landsat imagery, analyzing forest composition changes over a decade with greater accuracy and efficiency than deeper networks like VGG16 and ResNet. Another system,[9] the SimVP model, generated radar-based precipitation forecasts up to 120 minutes ahead, outperforming existing models across various precipitation scenarios, including heavy rainfall and typhoons. Lightweight CNNs were also developed for fast geometric correction and resolution enhancement of satellite images, significantly improving quality in terms of PSNR and processing speed. A two-step machine learning approach[10] using DINCAE and LGBM models effectively filled spatiotemporal gaps in sea surface temperature (SST) data, achieving high reconstruction accuracy ($R^2 = 0.98$) while minimizing overfitting. Lastly, a climatological and statistical analysis of typhoon paths over 40 years linked increased typhoon intensity to rising sea surface temperatures and El Niño events, reflecting the impact of global warming. Collectively, these studies highlight [11-15]the innovative use of AI and deep learning approaches to address complex environmental challenges, offering valuable tools for forecasting, mapping, and monitoring climate and environmental changes.

III. MATERIALS AND METHODS

The dataset borrowed from Kaggle data repository named as Imagery (2012-2021) (INSAT3D).[36]. It has 136 infrared images and 140 raw images of tropical cyclone images over the Indian Ocean from 2012 to 2021. This work considers infrared images only. The dataset used in 80:20 cross fold vadiation by using Weka3.9.6 tool for getting optimal solution.

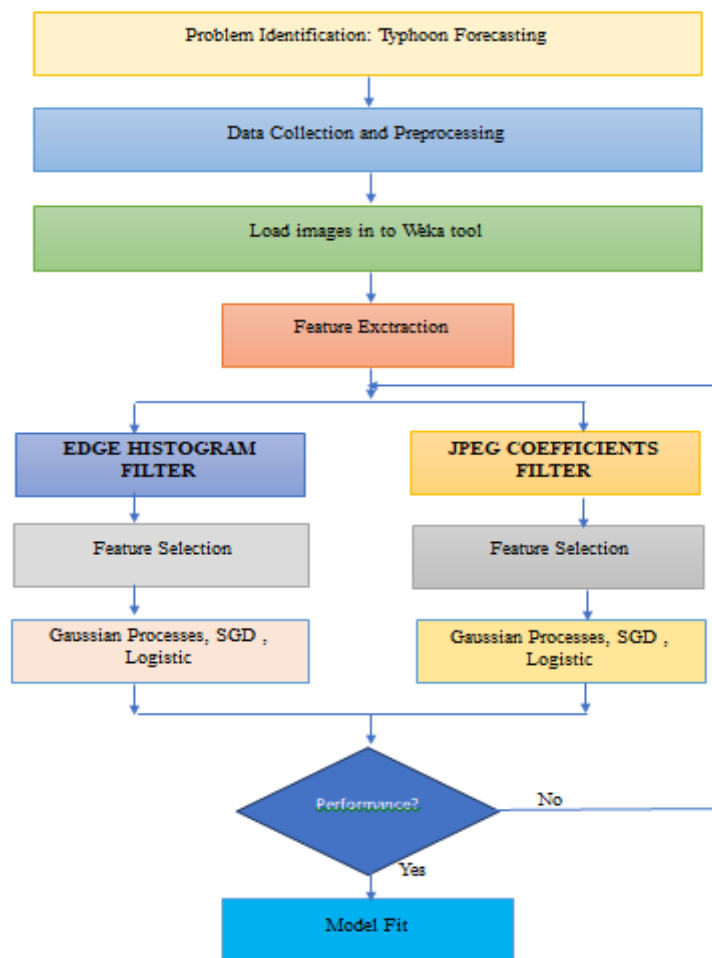


Figure 1: proposed system

The diagram outlines a machine learning-based algorithmic process for typhoon forecasting. It starts with problem identification followed by data collection and preprocessing. Images are loaded into the Weka tool for feature extraction, where two different filters are applied: the Edge Histogram Filter and the JPEG Coefficients Filter. Feature selection is performed, followed by model training using different algorithms such as Gaussian Processes, Stochastic Gradient Descent (SGD), and Logistic Regression. The performance of these models is evaluated, and the best-performing model is fit for final use. This approach leverages advanced feature extraction and selection techniques to optimize predictive accuracy.

Algorithm: Typhoon Forecasting using Machine Learning

Step 1: Problem Identification IdentifyProblem("Typhoon Forecasting")

Step 2: Data Collection and Preprocessing data = CollectAndPreprocessData("Typhoon Images, Weather Data")

Step 3: Load Images into Weka Tool wekaTool = Load_Images_Into_Weka(data)

Step 4: Feature Extraction features = Extract_Features(wekaTool)

Step 5: Apply Filters $edgeHistogramFeatures = ApplyFilter(features, "Edge Histogram Filter")$
 $jpegCoefficientsFeatures = ApplyFilter(features, "JPEG Coefficients Filter")$
Step 6: Feature Selection $selectedEdgeFeatures = FeatureSelection(edgeHistogramFeatures)$ $selectedJpegFeatures = FeatureSelection(jpegCoefficientsFeatures)$
Step 7: Model Training $modelsEdge = TrainModels(selectedEdgeFeatures, ["Gaussian Processes", "SGD", "Logistic Regression"])$ $modelsJpeg = TrainModels(selectedJpegFeatures, ["Gaussian Processes", "SGD", "Logistic Regression"])$
Step 8: Evaluate Model Performance $performanceEdge = EvaluateModelPerformance(modelsEdge)$ $performanceJpeg = EvaluateModelPerformance(modelsJpeg)$
Step 9: Select and Fit the Best Model if $performanceEdge > performanceJpeg$: $bestModel = FitModel(modelsEdge)$
 else: $bestModel = FitModel(modelsJpeg)$
Output: Final Fitted Model $OutputModel(bestModel)$

Table 1: Classification Metrics

S.No	Classifier	Accuracy	Precision	Recall	ROC	PRC	Time (In Sec)
1	Edge Histogram Filter with Gaussian Processes	79.93%	0.83	0.85	0.87	0.88	1.16
2	JPEG Coefficient Filter with Gaussian Processes	80.64%	0.84	0.86	0.89	0.89	1.07
3	Edge Histogram Filter with SGD	83.53%	0.86	0.88	0.89	0.89	1.12
4	JPEG Coefficient Filter with SGD	80.54%	0.81	0.87	0.86	0.85	2.11
5	Edge Histogram Filter with Logistic	76.75%	0.79	0.85	0.87	0.87	1.06
6	JPEG Coefficient Filter with Logistic	87.56%	0.89	0.89	0.95	0.99	2.98

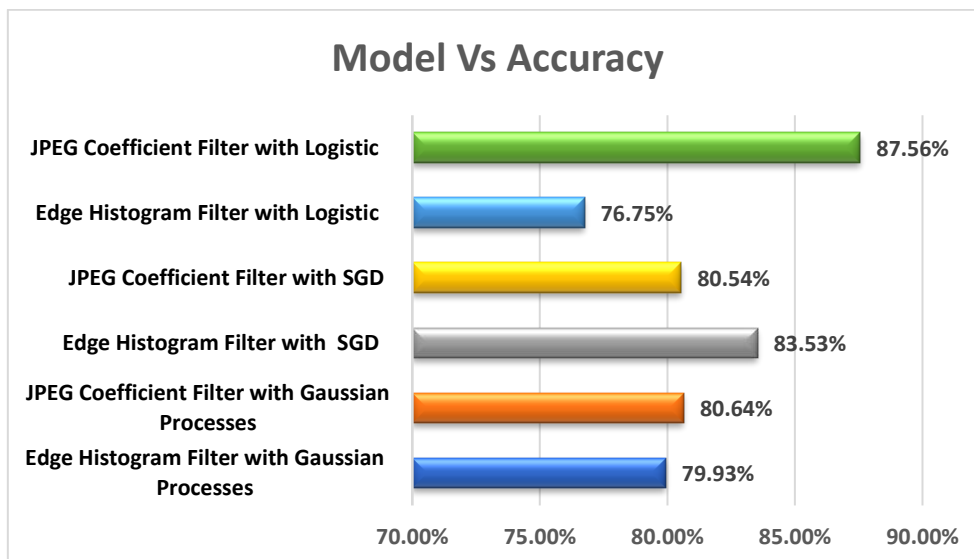


Figure 2: Model vs. Accuracy

The bar chart compares the accuracy of different classifiers used for typhoon forecasting based on the combination of filters and models. The "JPEG Coefficient Filter with Logistic" achieved the highest accuracy at 87.56%, significantly outperforming other models. In contrast, the "Edge Histogram Filter with Logistic" recorded the lowest accuracy at 76.75%.

76.75%. Other classifiers, such as "Edge Histogram Filter with SGD" and "JPEG Coefficient Filter with Gaussian Processes," demonstrated moderate performance, achieving 83.53% and 80.64% accuracy, respectively. This visualization clearly illustrates the effectiveness of combining specific filters and models for enhancing prediction accuracy, with the "JPEG Coefficient Filter with Logistic" emerging as the best-performing approach.

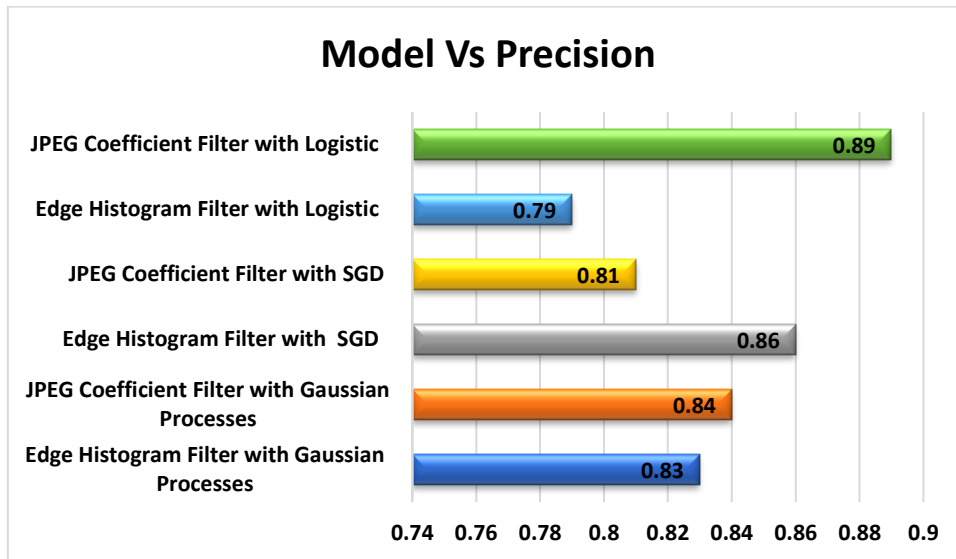


Figure 3: Model vs. Precision

The bar chart illustrates the precision of different classifiers used for typhoon forecasting. The "JPEG Coefficient Filter with Logistic" model achieved the highest precision at 0.89, indicating its strong ability to correctly identify true positives compared to other models. On the other end, the "Edge Histogram Filter with Logistic" exhibited the lowest precision at 0.79. The "Edge Histogram Filter with SGD" model also demonstrated a relatively high precision of 0.86, while "JPEG Coefficient Filter with Gaussian Processes" achieved a precision of 0.84. This comparison highlights the varying levels of precision across different filter and model combinations, with the "JPEG Coefficient Filter with Logistic" showing the best precision performance among the tested models.

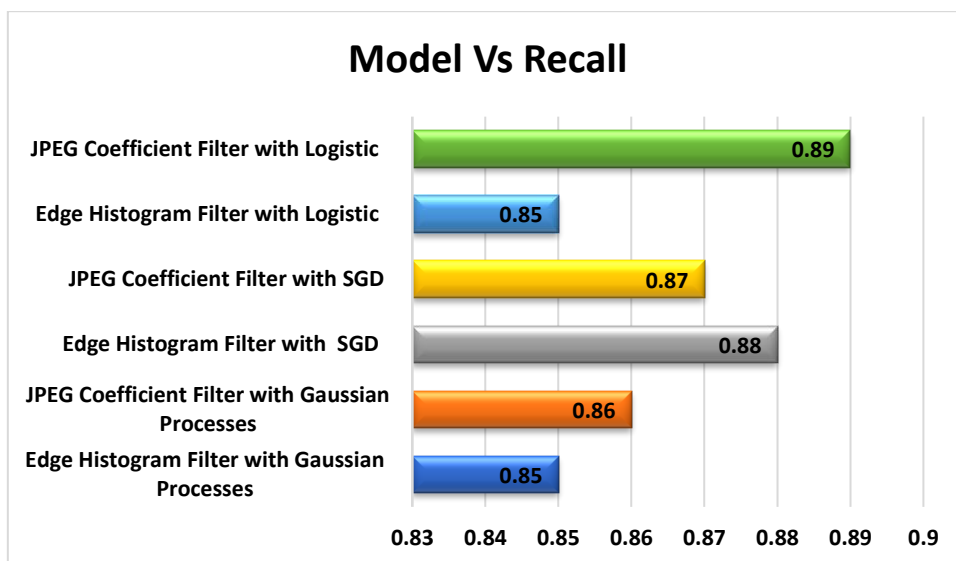


Figure 4: Model vs. Recall

The bar chart shows the recall values for different classifiers used in typhoon forecasting. The "JPEG Coefficient Filter with Logistic" classifier achieved the highest recall at 0.89, indicating its strong ability to correctly identify actual positive cases. The "Edge Histogram Filter with SGD" followed closely with a recall of 0.88, suggesting effective performance in terms of sensitivity. On the other end, both "Edge Histogram Filter with Logistic" and "Edge Histogram Filter with Gaussian Processes" demonstrated a lower recall of 0.85, showing less sensitivity compared to the top-performing models. This chart underscores the varying recall performances across different model-filter combinations, with the "JPEG Coefficient Filter with Logistic" consistently performing well in identifying relevant positive cases.

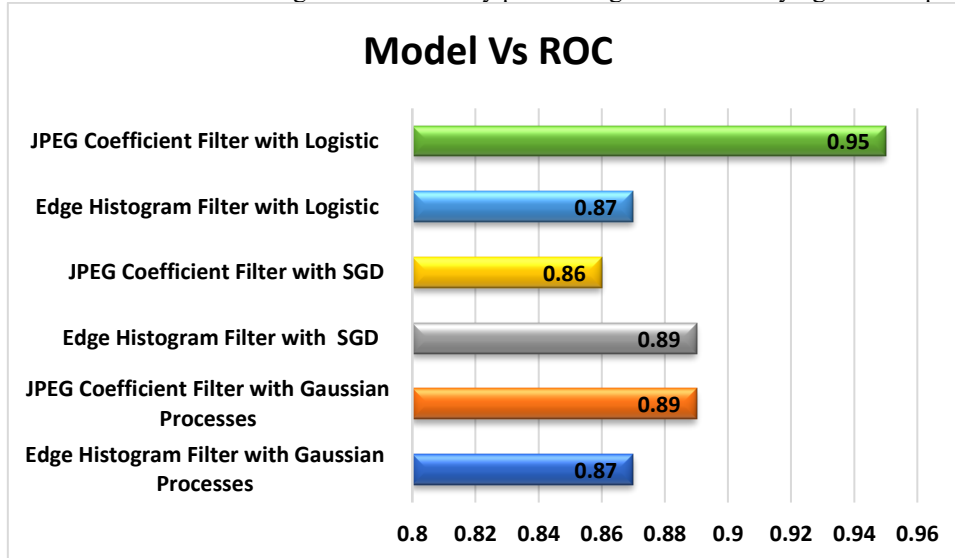


Figure 5: Model vs. ROC

The bar chart displays the ROC (Receiver Operating Characteristic) values for different classifiers used in typhoon forecasting. The "JPEG Coefficient Filter with Logistic" classifier stands out with the highest ROC value of 0.95, indicating exceptional discriminative ability in distinguishing between positive and negative cases. Other classifiers, such as the "Edge Histogram Filter with SGD" and "JPEG Coefficient Filter with Gaussian Processes," both achieved a notable ROC value of 0.89, showing strong predictive performance. In contrast, the "JPEG Coefficient Filter with SGD" exhibited a slightly lower ROC value of 0.86, while the "Edge Histogram Filter with Gaussian Processes" and "Edge Histogram Filter with Logistic" both scored 0.87. This chart highlights the superior performance of the "JPEG Coefficient Filter with Logistic" in terms of overall classification ability, as evidenced by its high ROC value.

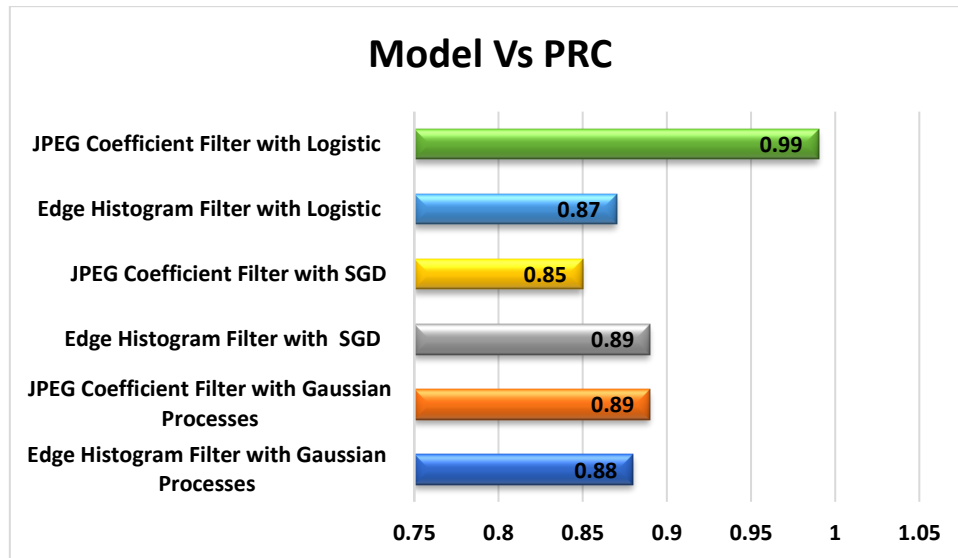


Figure 6: Model vs. PRC

The bar chart illustrates the PRC (Precision-Recall Curve) values for different classifiers in the context of typhoon forecasting. The "JPEG Coefficient Filter with Logistic" model achieved the highest PRC value of 0.99, reflecting its outstanding performance in maintaining precision across varying recall levels, which is crucial in scenarios with imbalanced classes. The "Edge Histogram Filter with SGD" and "JPEG Coefficient Filter with Gaussian Processes" both achieved a PRC value of 0.89, indicating strong but slightly lower performance. Other classifiers, such as "Edge Histogram Filter with Gaussian Processes" (0.88) and "Edge Histogram Filter with Logistic" (0.87), also performed relatively well. In comparison, the "JPEG Coefficient Filter with SGD" scored a lower PRC value of 0.85. Overall, this chart highlights the superior ability of the "JPEG Coefficient Filter with Logistic" in balancing precision and recall effectively, making it a strong performer among the tested models.

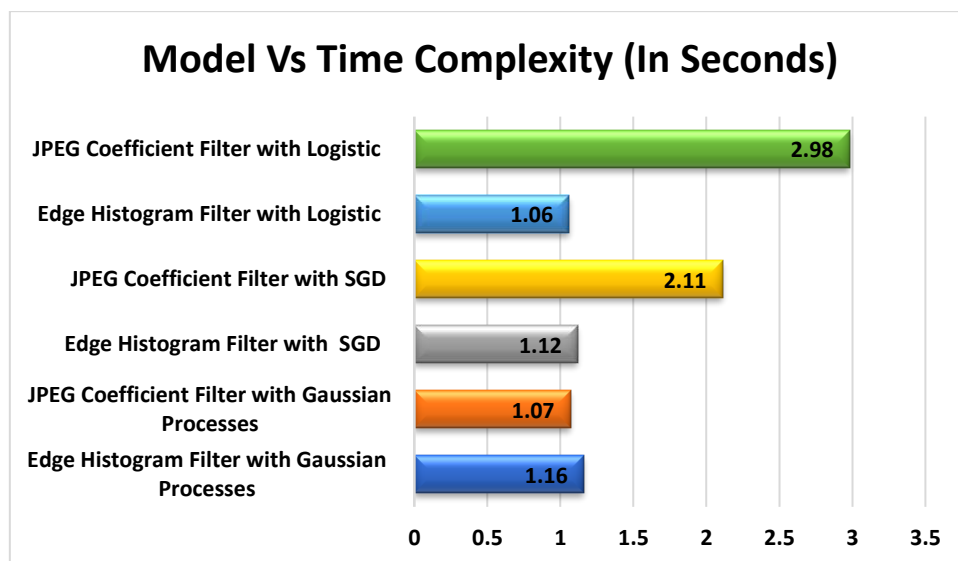


Figure 7: Model vs. Time Complexity

The bar chart presents the time complexity (in seconds) of different classifiers used in typhoon forecasting. The "JPEG Coefficient Filter with Logistic" model, while achieving high performance metrics, has the longest processing time at 2.98 seconds, indicating its computational intensity. In contrast, the "Edge Histogram Filter with Logistic" model has the shortest processing time at 1.06 seconds.

demonstrated a much faster processing time of 1.06 seconds, making it one of the most efficient models in terms of runtime. The "JPEG Coefficient Filter with SGD" took 2.11 seconds, reflecting moderate computational demand compared to other models. Meanwhile, "Edge Histogram Filter with SGD," "JPEG Coefficient Filter with Gaussian Processes," and "Edge Histogram Filter with Gaussian Processes" exhibited shorter times, ranging between 1.07 and 1.16 seconds. This chart highlights the trade-off between model performance and computational efficiency, with faster models potentially being more suitable for scenarios where quick predictions are crucial.

IV. CONCLUSION

This work concludes that the performance of different classifiers used in typhoon forecasting, focusing on combinations of filters and algorithms. Among all tested combinations, the "JPEG Coefficient Filter with Logistic" classifier achieved the highest accuracy at 87.56%, with strong precision, recall, and ROC values (0.89, 0.89, and 0.95, respectively), though it also exhibited the longest processing time at 2.98 seconds. In contrast, the "Edge Histogram Filter with Logistic" yielded the lowest accuracy (76.75%), though it performed reasonably well in terms of precision and recall. The "Edge Histogram Filter with SGD" demonstrated a relatively high accuracy of 83.53% with balanced precision and recall, while the "JPEG Coefficient Filter with Gaussian Processes" also showed solid performance at 80.64% accuracy, but with a shorter processing time of 1.07 seconds. The choice of classifier for typhoon forecasting depends on the desired balance between predictive performance and computational efficiency, with the "JPEG Coefficient Filter with Logistic" providing the best accuracy but at a higher computational cost.

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