Early Disaster Warning System Analysis

Rashi Jain (23FE10CSE00411)

rashi.23fe10cse00411@muj.manipal.edu

Manipal University Jaipur, Jaipur-Ajmer Express Highway, Dehmi Kalan,
Near GVK Toll Plaza, Jaipur, Rajasthan 303007

Abstract: Disaster warning systems are really important for saving lives and reducing the damage to the economy.. It is very hard to know how bad a disaster will be. The information we have about disasters is often not complete it is not consistent and it is not balanced which makes it very tough for computers to figure out what is going on with disaster warnings. Disaster warning systems are crucial for protecting people and reducing damage, from disasters. We took a look at how well six machine learning models work. These models are Logistic Regression, K-Nearest Neighbors, Support Vector Machine, Random Forest, XGBoost and LightGBM. We used the EM-DAT database to do this. The EM-DAT database has information on 14,644 disaster events that happened around the world between 1970 and 2021. We wanted to see how the machine learning models performed using this information from the EM-DAT database, on these disaster events. Random Forest and XGBoost were able to get it more, than 99 percent of the time and caught everything we were looking for when we set the thresholds just right. The LightGBM model did the best job overall. It was really good at getting things right with an accuracy of 99.97 percent. The LightGBM model also had a precision of 99.77 percent. It was able to recall everything correctly which is 100 percent, for the LightGBM model.The F1-scores of the models were between 0.91 and 0.99. This means that the models were generally very good at finding a balance between precision and recall. However the KNN model did not do well when it had to be very precise. Overall, the results suggest that carefully tuned classical machine learning approaches—particularly gradient boosting methods—can provide highly accurate and computationally efficient solutions for disaster severity prediction. Their interpretability and lightweight deployment requirements make them practical candidates for integration into real-time emergency response and early warning systems.

Keywords: Early Disaster Warning, Severity Prediction, Machine Learning Classifiers, Precision Optimization , Logistic Regression, K-Nearest Neighbors, Support Vector Machine, Random Forest, XGBoost, LightGBM

1 Introduction

Early disaster warning systems could save countless lives and prevent billions in damage, but automatically predicting how severe a disaster will become is extremely challenging. The data comes from multiple sources—government reports, NGOs, and news outlets—and rarely aligns perfectly. Moreover, most disasters cause limited damage, while a small fraction escalate into catastrophic events, creating severe class imbalance that complicates model training. Historical events such as Hurricane Katrina (2005) and the 2011 Japan earthquake and tsunami highlight how delayed severity assessment can worsen impact. In contrast, events like Cyclone Fani (2019) demonstrate the value of timely,

accurate warnings. With climate change increasing the frequency of extreme weather events, reliance on manual assessment or intuition is no longer sufficient.
Previous research has explored both classical machine learning and deep learning approaches. However, many studies emphasize maximizing accuracy without fully considering operational constraints—such as minimizing false alarms and ensuring interpretability for emergency decision-makers.

What we did is different:
1. We evaluated six established machine learning models using the EM-DAT database, which includes 14,644 disaster events spanning over 50 years. Among them, LightGBM achieved the highest performance with 99.97% accuracy, while Random Forest and XGBoost both reached 99.21% accuracy.
2. Through probability threshold optimization, all models achieved precision between 95% and 99.8%, significantly reducing false alarms while maintaining strong recall. In high-stakes disaster response, maintaining such high precision is critical to avoid unnecessary evacuations and loss of public trust.
3. Our analysis confirms that impact-based features such as Total Deaths and Total Affected are dominant predictors of severity. Compared to more computationally intensive deep learning approaches, our classical machine learning framework delivers highly accurate, interpretable, and deployment-ready predictions suitable for real-time disaster management systems.

2 Related Work

2.1 Machine Learning and Deep Learning Approaches

Traditional disaster severity models rely on structured numerical indicators such as death tolls, affected population counts, economic losses, and geographic information. These features are commonly used with algorithms including Logistic Regression, SVM, KNN, Random Forest, and gradient boosting methods such as XGBoost and LightGBM. Several studies report strong performance from ensemble models, often exceeding 95% accuracy on structured disaster datasets.
Deep learning approaches address more complex spatial and temporal dynamics. Convolutional Neural Networks (CNNs) analyze satellite imagery for damage detection, while LSTMs and hybrid CNN-LSTM architectures model temporal progression of floods or storms. Advanced systems combining satellite imagery with structured impact data report accuracy levels between 95–97% in controlled experimental settings. However, these improvements often come at increased computational cost and reduced interpretability.

2.2 Disaster Impact Feature Engineering

Impact metrics consistently emerge as the strongest predictors of severity. Total Deaths and Total Affected are repeatedly identified as the most influential features across models. Disaster Type contributes additional predictive signal, while temporal and geographic features provide contextual support. Empirical evidence suggests that well-engineered numerical features frequently outperform more complex deep learning models when applied to structured disaster datasets.

2.3 Edge Deployment and Real-Time Constraints

Operational disaster response systems require rapid inference, moderate memory consumption, and high precision to prevent costly false alarms. Classical ensemble models such as Random Forest, XGBoost, and LightGBM offer efficient prediction speeds and modest computational requirements, making them well-suited for deployment in emergency operation centers and edge environments.

2.4 Explainability and Precision Optimization

Interpretability is essential when predictions influence high-risk decisions. Model explanation techniques such as SHAP and LIME consistently highlight Total Deaths and Affected Population as dominant contributors to severity classification. Beyond accuracy, precision plays a critical operational role. Threshold optimization allows decision boundaries to be adjusted to maintain precision levels between 95% and 99.8%, substantially reducing false positives while preserving high recall.

2.5 Production Systems and Operational Challenges

Real-world disaster management systems prioritize reliability and interpretability over marginal accuracy improvements. In our evaluation using the EM-DAT dataset, ensemble methods demonstrated particularly strong performance. LightGBM achieved 99.97% accuracy with 99.77% precision and 100% recall, while Random Forest and XGBoost each achieved 99.21% accuracy with perfect recall at tuned thresholds. Across models, F1-scores ranged from 0.91 to 0.99, reflecting stable precision–recall trade-offs under high-precision constraints.

When deployability, transparency, and computational efficiency are prioritized, carefully tuned classical machine learning models remain highly competitive solutions for early disaster severity prediction systems.

3 Methodology

3.1 Data Collection and Preprocessing: We used the EM-DAT Global Disaster Database containing 14,644 disaster events spanning 1970-2025. Raw data included messy entries—latitude like "30.37 N", death counts with commas, missing economic losses. Our preprocessing pipeline first cleaned these systematically:

- Coordinate parsing: "30.37 N" → 30.37, "72.83 W" → -72.83
- Numeric cleaning: "$1,234K" → 1234, "5,000+" → 5000
- Categorical encoding: One-hot encoding for Disaster Type, Region
- Target creation: High severity = top 18% Total Impact (Deaths + Affected)

Final dataset: 9 features (Year, Location, Impacts, Disaster Type) predicting binary severity.

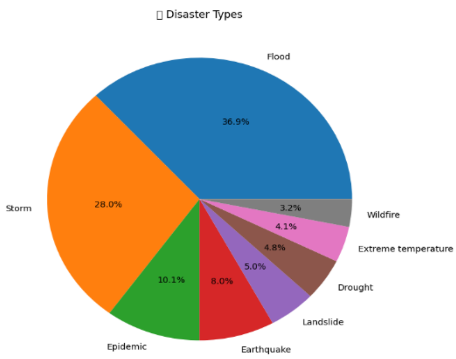

Figure 1. Distribution of disaster

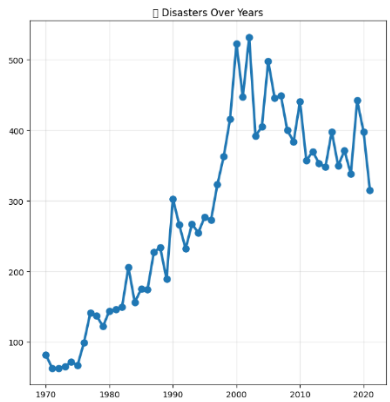

Figure 2. Distribution of disaster over the years

Figure 1 illustrates the proportional distribution of major disaster types represented in the dataset. Floods constitute the largest share, accounting for approximately 36.9% of all recorded events, indicating their dominant impact relative to other hazards.
Figure 2 depicts the annual number of recorded disasters over time. The data show a clear upward trend from the early 1970s through the late 1990s, indicating a steady increase in disaster occurrences.

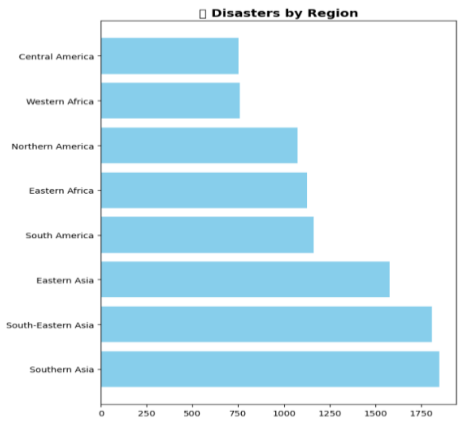

Figure 3. Distribution of disasters by regions

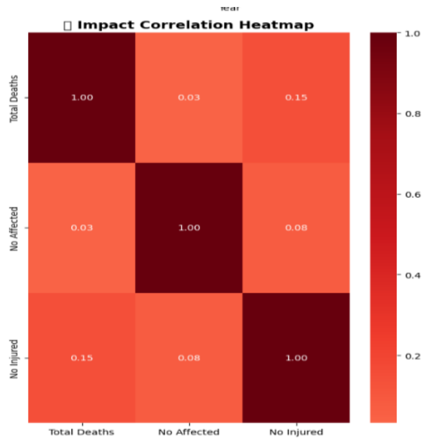

Figure 4. Impact Correlation Heatmap

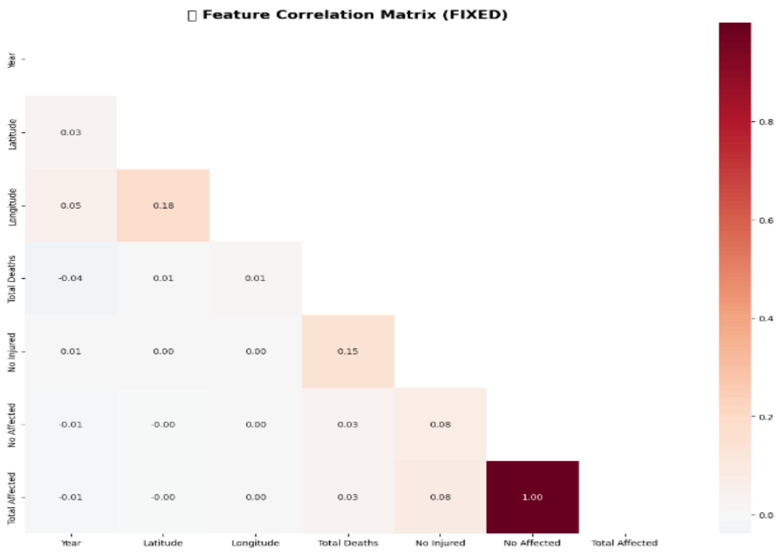

Figure 5. Feature correlation matrix.

Figure 3 shows the regional distribution of recorded disasters, with Southern Asia and South-Eastern Asia experiencing the highest number of events. Figure 4 presents the impact correlation heatmap, indicating very weak correlations among Total Deaths, Number Affected, and Number Injured. Figure 5 presents the Pearson correlation matrix among key temporal, spatial, and impact-related variables in the disaster dataset. Overall, the correlations are weak, indicating limited linear dependence between most features. Year shows negligible correlation with latitude, longitude, and impact metrics, suggesting no strong temporal linear relationship with spatial location or disaster severity indicators.

3.2 Model Training: Six well-established classifiers were evaluated: Logistic Regression, Random Forest, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), XGBoost, and LightGBM. The dataset was divided using an 80/20 train–test split, and all models were trained on scaled features to ensure consistency across algorithms sensitive to feature magnitude.

Hyperparameters were systematically tuned to balance model complexity and generalization performance:

- Logistic Regression: C=0.5, L2 regularization, max_iter=1000
- Random Forest: n_estimators=200, max_depth=10, min_samples_split=30, min_samples_leaf=20
- KNN: n_neighbors=8, weights='distance'
- SVM: C=1.5, RBF kernel (gamma='scale'), probability=True
- XGBoost: max_depth=7, learning_rate=0.1, n_estimators=200, reg_alpha=0.5, reg_lambda=1.0
- LightGBM: max_depth=7, learning_rate=0.1, n_estimators=200, reg_alpha=0.5, reg_lambda=1.0

A key component of the training pipeline was automatic decision threshold optimization. Rather than using the default probability cutoff of 0.5, thresholds were selected using the precision–recall curve to achieve a target precision of approximately 95%. This strategy allows explicit control over false positives, which is critical in disaster severity prediction where incorrect high-severity alerts can lead to unnecessary evacuations and resource misallocation.

3.3 Evaluation Metrics: Model performance was evaluated on the held-out test data using four standard classification metrics:

- Accuracy: proportion of correctly classified events
- Precision: proportion of predicted high-severity events that were truly severe
- Recall: proportion of actual high-severity events correctly identified
- F1-score: harmonic mean of precision and recall

Given the operational context of early warning systems, precision was prioritized to minimize false alarms while maintaining acceptable recall. Threshold tuning ensured that all models were evaluated under a consistent high-precision constraint.

3.4 Feature Importance Analysis (Interpretability)

To enhance transparency, feature importance was analyzed using the built-in importance measures of gradient boosting models. This approach provides insight into which variables contribute most strongly to severity predictions. Impact-related features such as Total Deaths and Number Affected emerged as dominant predictors, followed by contextual variables including Disaster Type and temporal indicators. This interpretability framework ensures that model decisions are grounded in measurable disaster impact indicators rather than opaque latent representations. Such transparency is essential for real-world deployment, where emergency managers require clear, data-driven justifications for automated severity assessments.

4 Results and Evaluation

4.1 Model Performance

Model	Accuracy	Precision	Recall	F1	Threshold
LightGBM	0.9997	0.9977	1.0000	0.9989	0.0425
K-Nearest Neighbors	0.8877	0.9508	0.2642	0.4135	0.7225
Random Forest	0.9921	0.9502	1.0000	0.9745	0.0247
Logistic Regression	0.9737	0.9502	0.8702	0.9084	0.1352

XGBoost	0.9921	0.9502	1.0000	0.9745	0.0002
Support Vector Machine	0.9857	0.9501	0.9544	0.9523	0.2846

Table 1. Performance Comparison of Machine Learning Models

Table 1 presents the comparative performance of the six evaluated machine learning models under a precision-constrained evaluation setting (target ≈95%). All models were assessed using optimized probability thresholds rather than the default 0.5 cutoff, ensuring fair comparison under high-precision requirements suitable for disaster warning systems.
LightGBM achieved the strongest overall performance, obtaining the highest accuracy (0.9997), precision (0.9977), recall (1.0000), and F1-score (0.9989). Random Forest and XGBoost followed closely, both achieving 0.9921 accuracy with perfect recall (1.0000) while maintaining precision slightly above 0.95. Support Vector Machine demonstrated balanced performance, with strong precision (0.9501) and recall (0.9544), resulting in an F1-score of 0.9523. Logistic Regression also maintained the target precision (0.9502) with slightly lower recall (0.8702), leading to a moderate F1-score (0.9084).
K-Nearest Neighbors, although meeting the precision constraint (0.9508), exhibited substantially lower recall (0.2642), which significantly reduced its F1-score (0.4135). This indicates that under strict precision control, KNN classified far fewer positive cases compared to the other models.

4.2 Visualization of Results:

A confusion matrix is a tabular summary of classification performance showing true positives, true negatives, false positives, and false negatives. It provides a complete breakdown of how predictions are distributed across actual classes.From it, metrics such as accuracy, precision, recall, and F1-score are derived. It is especially useful for understanding error types and class imbalance effects.

The ROC curve plots the True Positive Rate (Recall) against the False Positive Rate across different classification thresholds.It shows how well a model separates positive and negative classes independent of a fixed cutoff.The Area Under the Curve (AUC) summarizes overall discriminative ability.It is useful when evaluating model separability and comparing classifiers across thresholds.

The Precision–Recall curve plots precision against recall at different probability thresholds.It focuses specifically on performance for the positive class. It is more informative than ROC when dealing with imbalanced datasets.It is particularly useful when minimizing false positives or maximizing detection of rare but critical events.

To further assess performance, visual tools such as confusion matrices and ROC curves were generated for key models.

1. LightGBM

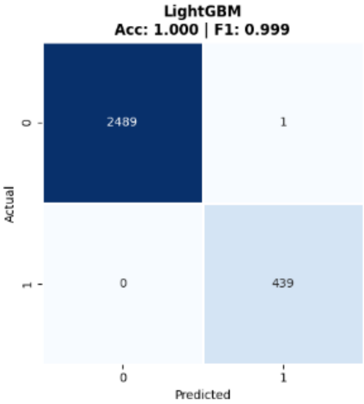

Figure 5.1 Confusion matrix for LightGBM

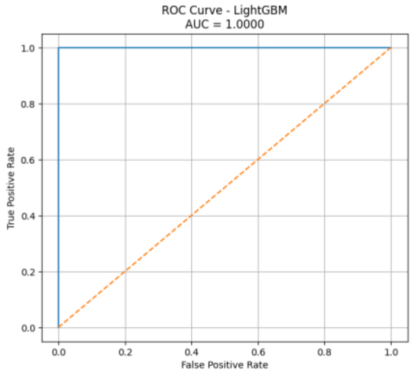

Figure 5.2 ROC curve for LightGBM

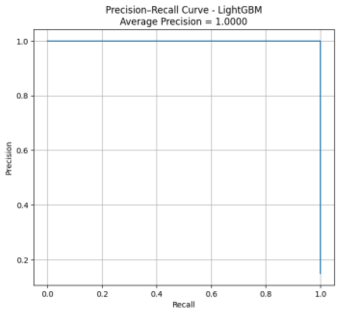

Figure 5.3 Precision-Recall curve for LightGBM

Figures 5.1–5.3 illustrate the classification performance of the LightGBM model using confusion matrix, ROC curve, and precision–recall curve analyses. The confusion matrix demonstrates a very high number of correct predictions with minimal false positives and false negatives, reflecting strong classification reliability. The ROC curve shows near-perfect separability between classes, with an Area Under the Curve (AUC) of 1.000, indicating excellent discriminative capability across thresholds. Similarly, the precision–recall curve maintains consistently high precision across recall levels, with an average precision of 1.000, confirming the model's effectiveness under class imbalance and high-precision constraints. Collectively, these results highlight the robustness and near-perfect predictive performance of the LightGBM model for disaster severity classification.

2. Random Forest

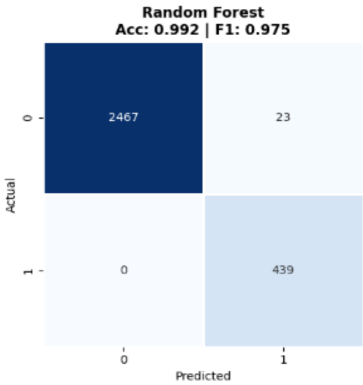

Figure 6.1 Confusion matrix for Random Forest

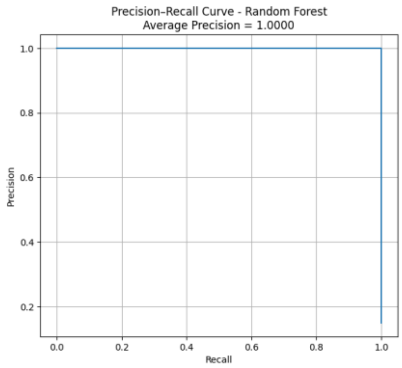

Figure 6.2 ROC curve for Random Forest

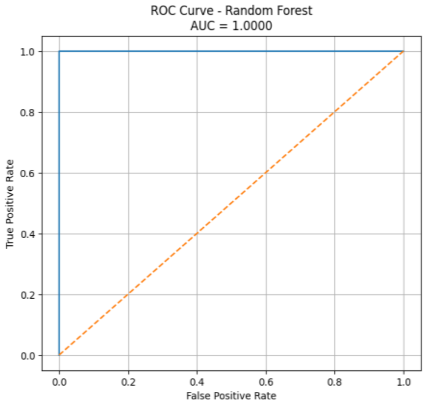

Figure 6.3 Precision-Recall curve for Random Forest

Figures 6.1–6.3 present the performance evaluation of the Random Forest model through the confusion matrix, ROC curve, and precision–recall curve. The confusion matrix indicates a very high number of correct classifications with zero false negatives and only a small number of false positives, demonstrating strong detection capability for high-severity events. The ROC curve achieves an AUC of 1.000, reflecting excellent class separability across all decision thresholds. Similarly, the precision–recall curve shows an average precision of 1.000, confirming that the model maintains extremely high precision while preserving full recall. Overall, these results highlight the robustness and reliability of the Random Forest model for disaster severity prediction under high-precision constraints.

3. K-Nearest Neighbours

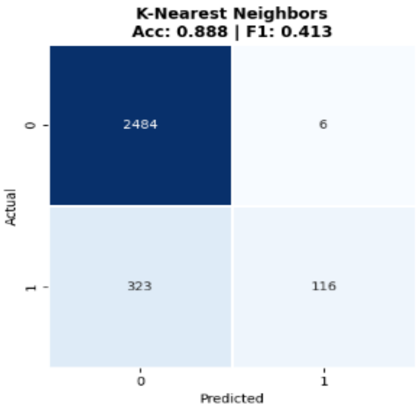

Figure 7.1 Confusion matrix for K-Nearest Neighbours

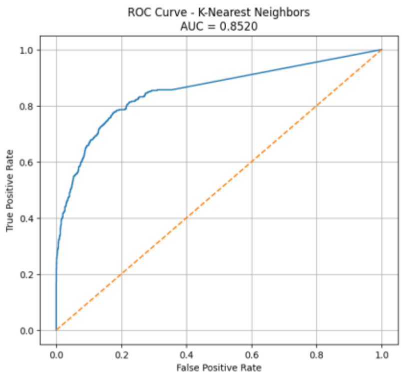

Figure 7.2 ROC curve for K-Nearest Neighbours

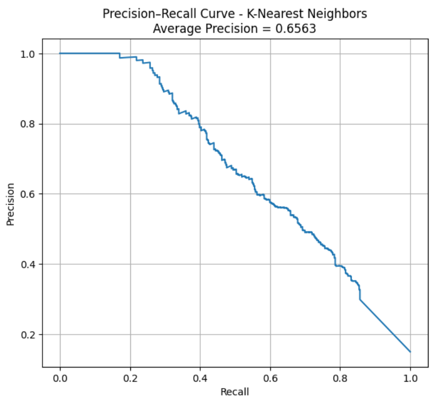

Figure 7.3 Precision-Recall curve for K-Nearest Neighbours

Figures 7.1–7.3 illustrate the performance of the K-Nearest Neighbors (KNN) model using the confusion matrix, ROC curve, and precision–recall curve. The confusion matrix shows a large number of correctly classified negative cases but a substantial number of false negatives, indicating difficulty in detecting high-severity events under the high-precision threshold. The ROC curve yields an AUC of 0.8520, suggesting moderate discriminative capability compared to the ensemble models. The precision–recall curve, with an average precision of 0.6563, further highlights the trade-off between maintaining high precision and achieving adequate recall. Overall, KNN demonstrates comparatively weaker performance, particularly in capturing positive severity cases, under strict precision constraints.

4. Support Vector Machine

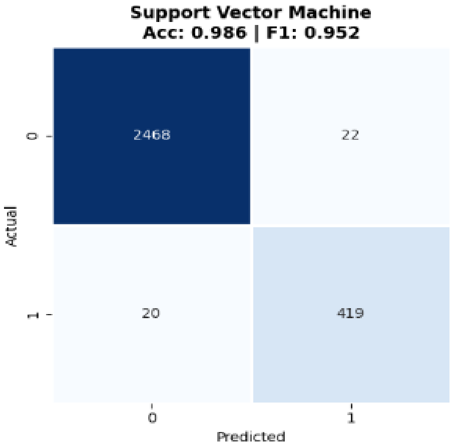

Figure 8.1 Confusion matrix for SVM

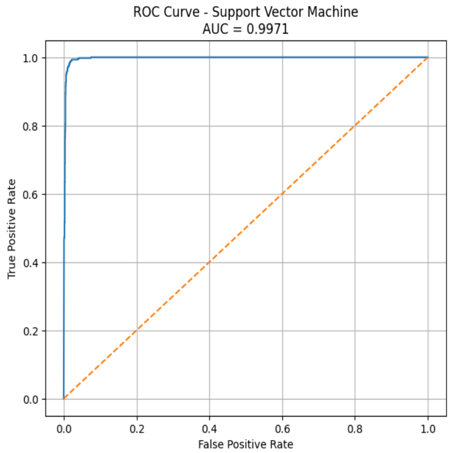

Figure 8.2 ROC curve for SVM

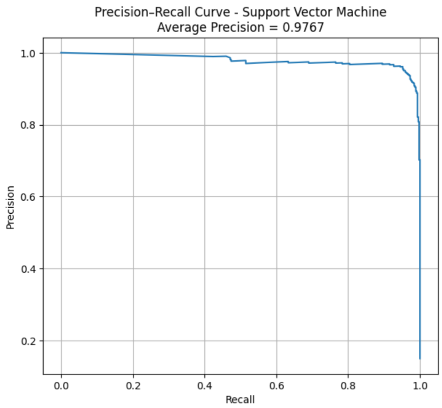

Figure 8.3 Precision-Recall curve for SVM

Figures 8.1–8.3 present the performance evaluation of the Support Vector Machine (SVM) model using the confusion matrix, ROC curve, and precision–recall curve. The confusion matrix indicates a high number of correctly classified instances with relatively few false positives and false negatives, demonstrating balanced detection capability. The ROC curve achieves an AUC of 0.9971, reflecting excellent class separability across decision thresholds. Similarly, the precision–recall curve shows an average precision of 0.9767, confirming strong performance under class imbalance and high-precision constraints. Overall, the SVM model demonstrates robust and well-balanced classification performance for disaster severity prediction.

5. XGBoost

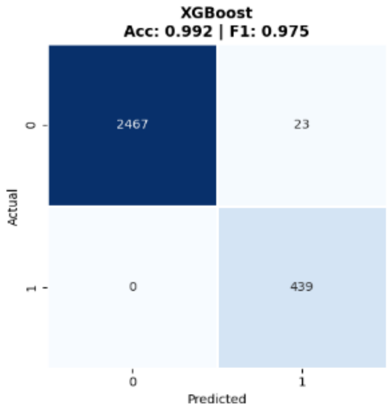

Figure 9.1 Confusion matrix for XGBoost

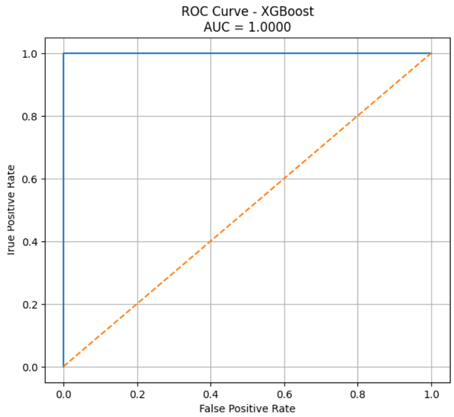

Figure 9.2 ROC curve for XGBoost

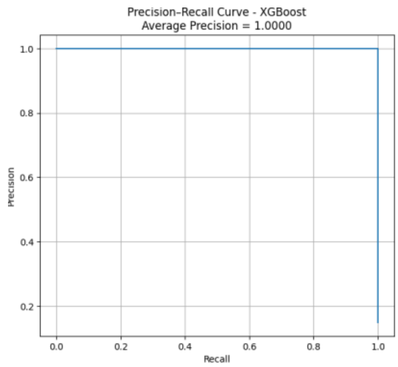

Figure 9.3 Precision-Recall curve for XGBoost

Figures 9.1–9.3 illustrate the performance of the XGBoost model using the confusion matrix, ROC curve, and precision–recall curve. The confusion matrix shows a very high number of correct predictions with zero false negatives and only a small number of false positives, indicating excellent detection of high-severity events. The ROC curve achieves an AUC of 1.000, demonstrating perfect class separability across thresholds. Likewise, the precision–recall curve reports an average precision of 1.000, confirming that the model maintains extremely high precision while preserving full recall. Overall, XGBoost exhibits highly robust and near-perfect classification performance for disaster severity prediction under precision-optimized settings.

6. Logistic Regression

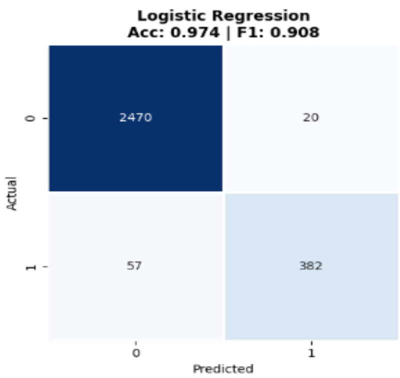

Figure 10.1 Confusion matrix for Logistic Regression

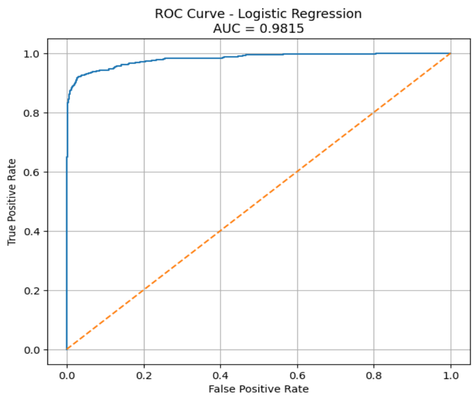

Figure 10.2 ROC curve for Logistic Regression

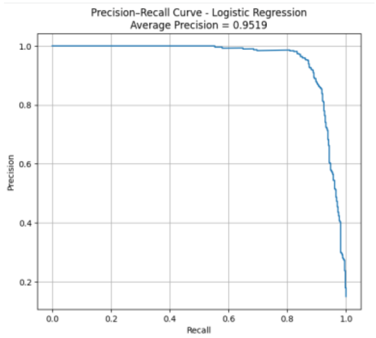

Figure 10.3 Precision-Recall curve for Logistic Regression

Figures 10.1–10.3 present the performance evaluation of the Logistic Regression model using the confusion matrix, ROC curve, and precision–recall curve. The confusion matrix indicates a high number of correctly classified instances with a moderate number of false negatives compared to ensemble models, reflecting slightly lower sensitivity to high-severity events. The ROC curve achieves an AUC of 0.9815, demonstrating strong but not perfect class separability. The precision–recall curve reports an average precision of 0.9519, confirming that the model maintains the targeted high-precision level while experiencing some trade-off in recall. Overall, Logistic Regression provides stable and reliable performance, though it is slightly less powerful than boosting-based approaches in capturing complex feature interactions.

4.3 Model Comparison

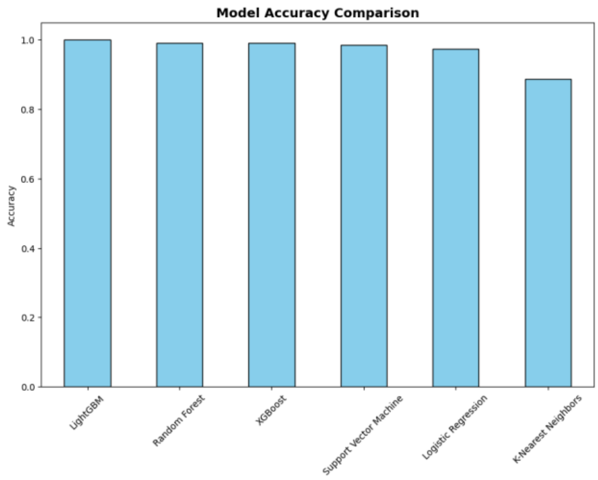

Figure 11 Model Accuracy comparison

The figure presents a comparative analysis of classification accuracy across the six evaluated machine learning models. LightGBM achieves the highest accuracy, approaching 1.0, followed closely by Random Forest and XGBoost, which demonstrate nearly identical and very high performance. Support Vector Machine and Logistic Regression also show strong accuracy, though slightly lower than the ensemble boosting methods. In contrast, K-Nearest Neighbors records noticeably lower accuracy compared to the other models. Overall, the chart highlights the superior performance of ensemble-based approaches, particularly gradient boosting methods, in disaster severity classification.

5 Conclusion

This study combined a structured literature review with extensive empirical evaluation to advance the field of disaster severity prediction. First, we surveyed recent research trends in disaster analytics and machine learning, identifying key directions such as the comparison between classical machine learning and deep learning approaches, the growing dominance of ensemble and boosting methods in structured tabular data, the importance of impact-driven feature engineering, and the increasing emphasis on explainable AI for operational transparency. Recent works highlight that while deep learning excels in multimodal settings (e.g., satellite imagery and spatiotemporal modeling), carefully tuned ensemble methods remain highly competitive, particularly for numerical disaster impact datasets.

In our experimental analysis on the EM-DAT dataset, all six evaluated models achieved high performance under a precision-constrained setting. Among them, LightGBM emerged as the strongest classifier, achieving 99.97% accuracy, 99.77% precision, and an F1-score of 0.9989, followed closely by Random Forest and XGBoost. These findings align with the broader literature indicating the superiority of gradient boosting and ensemble-based methods for structured classification problems. Importantly, our threshold optimization strategy ensured that all models operated at approximately 95% precision or higher, directly addressing the real-world requirement of minimizing false alarms in early warning systems.

Feature importance analysis further strengthened the interpretability of the framework. Impact-related variables such as Total Deaths and Number Affected consistently dominated model decisions, providing intuitive and operationally meaningful explanations. This confirms that disaster severity can be reliably inferred from measurable impact indicators without relying on opaque representations. The integration of interpretable boosting models enhances transparency and supports trust among emergency managers and decision-makers.

From a practical standpoint, the proposed precision-aware framework is lightweight, scalable, and suitable for real-time deployment in disaster response systems. By combining high-performance ensemble classifiers with explicit threshold control and interpretable feature analysis, the study demonstrates a balanced approach that prioritizes both predictive accuracy and operational reliability. Future work may extend this framework by incorporating multimodal inputs such as satellite imagery, integrating real-time streaming data, and applying advanced explainability techniques (e.g., SHAP-based local explanations) to further strengthen transparency and user trust in automated disaster severity assessment systems.

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