Modelling Disaster Severity using Machine Learning Models

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1 ABSTRACT

Disasters—both natural and man-made—pose severe challenges to global societies, causing significant loss of life, economic disruption, and population displacement. As the frequency and intensity of disasters escalate due to climate change, urbanization, and population growth, traditional disaster management approaches often fall short in capturing the complexities of disaster impacts. This project presents a comprehensive framework for disaster severity modeling by integrating unsupervised clustering, supervised ensemble learning, and time series analysis. Using K-means clustering, a high Silhouette Score of over 90% was achieved, effectively grouping disaster events based on severity metrics. A stacking ensemble model, combining Random Forest, Gradient Boosting, and a meta-model of Logistic Regression, achieved a testing accuracy of 80% on earthquake data and 73% on tsunami data, demonstrating its robustness in predicting disaster severity. Additionally, time series analysis was conducted to visualize severity trends over time for earthquakes and tsunamis, highlighting valuable patterns and temporal insights. The outcomes of this study emphasize the potential of machine learning and temporal analysis in understanding disaster dynamics and aiding decision-making processes for disaster risk reduction.

2 INTRODUCTION

In an era of increasing environmental uncertainty, disasters such as earthquakes, floods, tsunamis, and droughts pose significant and growing threats to societies worldwide. These catastrophic events claim countless lives, displace entire populations, and inflict severe economic and infrastructural damage. The intensifying frequency and magnitude of disasters, driven by climate change, rapid urbanization, and population growth, demand innovative and efficient strategies for disaster preparedness, response, and mitigation. Governments, humanitarian organizations, and emergency responders face mounting pressure to allocate resources effectively, minimize losses, and enhance resilience against these unpredictable events.

Accurately estimating disaster severity is a cornerstone of effective disaster management, enabling better resource allocation, early warning systems, and risk reduction measures. Traditional approaches to disaster management, however, often rely on historical data and heuristic-based models that fail to capture the multifaceted and dynamic nature of disaster impacts. These methods struggle with high-dimensional data, imbalanced metrics, and the time-dependent trends that are critical to understanding the evolving nature of disasters.

This project addresses these challenges by employing a comprehensive framework that integrates machine learning and time series analysis to model disaster severity. Unsupervised learning techniques, such as K-means clustering, identify latent patterns in historical disaster data, grouping events based on severity metrics such as casualties, economic losses, and damages. A stacking ensemble model, combining Random Forest, Gradient Boosting, and Logistic Regression as a meta-model, delivers robust supervised learning predictions, achieving testing accuracies of 80% on earthquake data and 73% on tsunami data. Time series analysis further enriches this framework by visualizing temporal trends in predicted severity, uncovering seasonal variations and long-term patterns.

By leveraging the strengths of clustering, supervised learning, and temporal analysis, this project offers a scalable and data-driven approach to disaster severity modeling. The insights generated through this framework have the potential to significantly improve disaster preparedness and response strategies, contributing to global efforts in disaster risk reduction and resilience-building.

3 RELATED WORK

3.1 Time Series Analysis Techniques

Various time series analysis techniques have been utilized in disaster prediction, including:

3.1.1 Statistical Methods. Autoregressive Integrated Moving Average (ARIMA) is often employed in the forecasting of data that varies with time. Box and Jenkins's 1970 [1] study set the foundation for its use in natural disaster prediction. Seasonal Decomposition of Time Series (STL) is very popular as well. Studies by Cleveland et al. [2] demonstrate that STL is used to remove seasonal components, which facilitates the identification of underlying trends.

3.1.2 Machine Learning Approaches. Support Vector Machines (SVM): Showing encouraging results when used for earthquake prediction [3]. SVMs enhance predicting accuracy by efficiently handling non-linear data. Artificial neural networks (ANN): It has been demonstrated that ANNs, when applied to complicated patterns in data, perform better in flood prediction than conventional techniques [4].

3.1.3 Hybrid Models. Hybrid models that mix statistical and machine learning methods—have been the subject of recent research.

For example, a hybrid ARIMA-ANN model that enhanced typhoon intensity prediction accuracy was proposed by Chen et al. [5].

3.2 Applications in Disaster Prediction

3.2.1 Earthquake Prediction. The use of seismic data in time series models for earthquake prediction has been investigated in a number of research. Recurrent neural networks (RNNs) are a noteworthy method for analysing seismic wave patterns [6].

3.2.2 Flood Forecasting. Hydrological data collected in real time has been crucial for flood prediction. Flooding events have been accurately predicted using a time series model and data from remote sensing [7].

3.2.3 Hurricane Intensity Forecasting. Kossin et al.'s [8] research highlights the value of time series analysis in predicting hurricane intensity by combining climate variables with historical hurricane data.

3.3 Challenges

Despite significant progress in developing the disaster severity prediction system, several challenges were encountered that require further attention and refinement:

Data Imbalance Severe disasters are underrepresented in the dataset compared to minor events, creating challenges in model training. Addressing this requires:

- Employing resampling techniques, such as oversampling or undersampling, to balance the dataset.
- Exploring specialized loss functions, such as `Focal Loss`, to mitigate biases towards majority classes.

Heterogeneous Data Sources Integrating structured data (e.g., numerical tables) and unstructured data (e.g., social media posts, images) posed preprocessing and alignment challenges. To ensure consistency:

- Advanced data integration frameworks and preprocessing pipelines are necessary.
- Feature alignment techniques, such as embedding representations, can be leveraged to combine diverse data types effectively.

Data Availability Sourcing reliable data from underrepresented regions and disaster types remains a significant hurdle. This is especially challenging for remote or underdeveloped areas. Potential solutions include:

- Leveraging satellite imagery and IoT sensor data to enhance data coverage.
- Incorporating crowd-sourced information from platforms like social media to fill gaps in traditional datasets.

Addressing these challenges is crucial to improving the system's predictive accuracy, generalizability, and real-world applicability.

4 PROPOSED WORK

This research focuses on developing a predictive system for disaster severity using a combination of unsupervised and supervised machine learning techniques, along with time series analysis. The goal is to leverage historical disaster data to build a robust model that not only predicts the severity of future disasters but also identifies regions that require more financial aid for disaster recovery.

4.1 Data Preprocessing:

4.1.1 Dataset Overview. The dataset for this study was sourced from NGDC NOAA and includes data on various disaster types, severity levels, and related attributes. Initial observations revealed missing values, irrelevant columns, and skewness in disaster type distribution.

4.1.2 Cleaning Techniques. To improve data quality, the following techniques were applied:

Column Removal: Removed unhelpful fields such as "Volcano Name" and "Death Description" to reduce noise.
Handling Missing Values: Mean Imputation: Used for symmetric data like "No. of Deaths".
Median Imputation: Effective for skewed columns, e.g., "No. Homeless".
Manual Filling: Filled categorical fields (e.g., Magnitude Scale) with default values like 'Unknown'.
Group-Based Filling: Applied country-specific means for fields like Latitude and Longitude.
These methods minimized bias and ensured a clean, balanced dataset for modeling.

4.2 Statistical Analysis and Correlation

To understand the relationships between various disaster-related parameters, correlation analysis was conducted using contingency tables and the Chi-Square test of independence. Key variables analyzed include *Disaster Type*, *Location*, *Total Damage*, *Magnitude*, *Total Deaths*, *AID Contribution*, *Reconstruction Costs*, and *Insured Damage*.

For this analysis, contingency tables were constructed for pairs of variables such as *Disaster Type* vs. *Location* and *Total Damage* vs. *Magnitude*. The Chi-Square test was performed on each table to evaluate whether a statistically significant association exists between the variables. The test outputs included the Chi-Square statistic, degrees of freedom, and the p-value. A significance level of 0.05 was used to determine statistical significance.

Key findings from the analysis include:

- A significant association was found between *Disaster Type* and *Location*, suggesting that certain disaster types are more prevalent in specific regions.
- The relationship between *Total Damage* and *Magnitude* was also statistically significant, highlighting the proportional impact of disaster severity.
- Statistically significant associations were observed between *Total Deaths* and *AID Contribution*, as well as *Reconstruction Costs* and *Total Deaths*, emphasizing the role of human casualties in driving post-disaster financial support and rebuilding efforts.
- No significant association was detected between *Total Affected* and *Location*, nor between *Insured Damage* and *Total*

Damage, indicating these relationships may not be direct or require further nuanced modeling.

4.3 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is a crucial step in understanding the dataset's structure and characteristics. It helps in uncovering patterns, detecting outliers, and testing assumptions through visual and statistical methods. In this analysis, we examine disaster-related data, focusing on disaster types, their frequency across regions, and the total damage and deaths caused by these disasters. We also analyze earthquake data, looking at earthquake magnitudes, their impact, and correlations with other variables.

4.3.1 Data Visualization.

Regional Focus: Disaster data was aggregated by region to identify geographic patterns. The last part of the `Location` column was extracted to approximate the region or country. Key steps included:

- Extracting disaster frequency for the top 10 most affected regions.
- Calculating the frequency of each disaster type within these regions.
- Visualizing associations using bar plots to display the most frequent disaster types by region.

Disaster Frequency Analysis by Region: We started by analyzing the frequency of disasters across different regions:

Top 10 Regions by Frequency of Disasters: We identified the top 10 regions with the highest number of disaster occurrences. A bar plot was created to visualize the most frequent disaster types for each region. The top regions typically included high-frequency disaster types like floods and storms, which are known to occur more frequently.

Key Insights: Regions like South Asia, Central America, and parts of Africa show a higher frequency of natural disasters, with floods and storms being the most common. These patterns indicate that specific regions are more vulnerable to certain types of natural events.

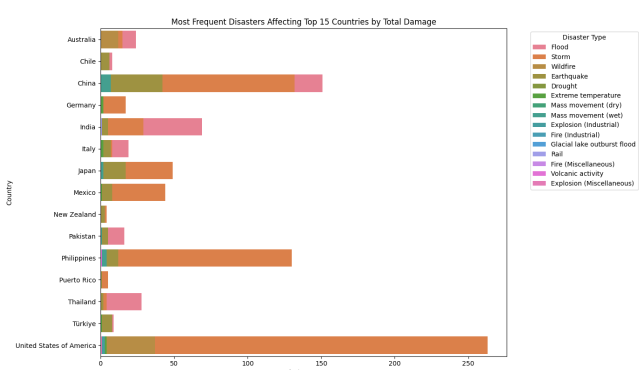

Figure 1: Most Frequent Disasters Affecting Top 15 Countries by Total Deaths

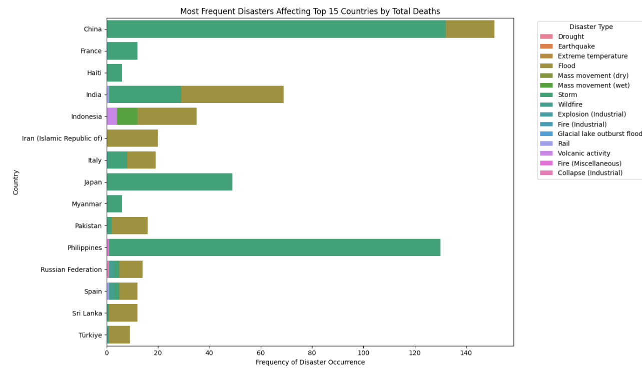

Figure 2: Most Frequent Disasters Affecting Top 15 Countries by Total Damage

Disaster Impact by Region and Country: We analyzed the total damage and deaths caused by disasters across different regions and countries:

Top 10 Regions by Total Damage: We grouped disaster impact by region and plotted the total damage caused by disasters in the top 10 regions. This plot showed regions like East Asia and the Pacific as having the highest damage totals.

Top 10 Regions by Total Deaths: Similarly, we identified regions with the highest number of deaths due to disasters. This visual analysis highlighted regions in South Asia and Africa as experiencing the most significant loss of life.

Key Insights:

The regions that experience the most damage and deaths often correlate with areas exposed to both natural hazards and poverty, which exacerbates the impact. Certain regions are more prone to large-scale catastrophic events, which result in both high death tolls and extensive damage.

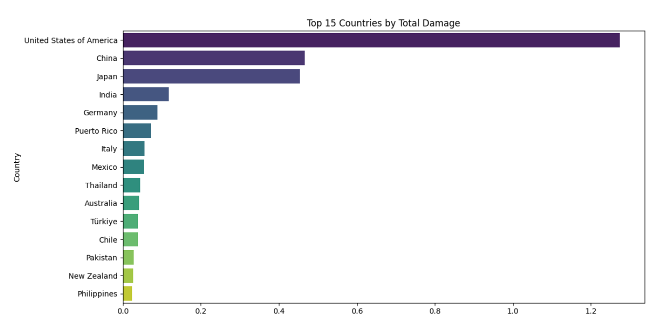

Figure 3: Top 15 Countries by Total Damage

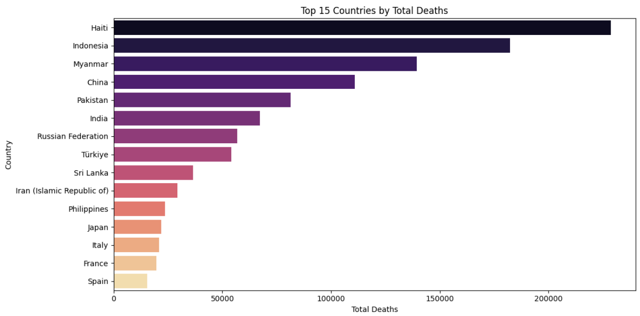

Figure 4: Top 15 Countries by Total Deaths

Aid Contribution Analysis: The analysis of financial aid contribution to disaster relief was carried out as follows:

Aid Contribution by Country: We aggregated the aid contributions by country and visualized the top 20 countries by their aid contributions using a bar chart.

Key Insights:

Wealthier nations or those with higher disaster occurrences tend s to contribute more aid. The top contributors often include countries with the resources to provide disaster relief globally. we can see that Indonesia has many deaths, but its government aid is less. here we achieve that analysis of countries having damage but not much funding

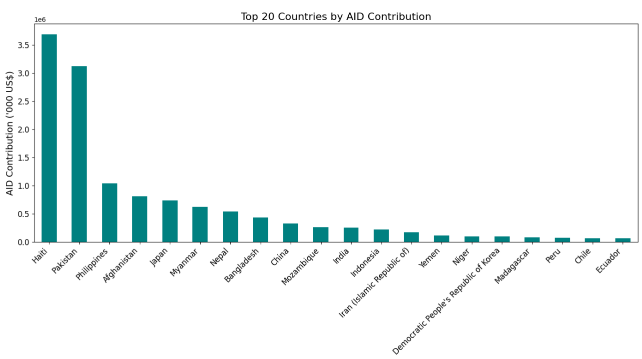

Figure 5: Top 20 Countries by AID Contribution

Skewness in Disaster Type Data. To understand the distribution of disaster types:

Skewness: We calculated the skewness of the distribution of disaster types and visualized the count of each disaster type in a bar chart. The skewness value indicated that the data was highly positively skewed, meaning certain disaster types, such as floods and storms, occurred more frequently than others.

Key Insights:

The skewness confirmed that the data is dominated by a few disaster types. While this result is expected, given the higher frequency of floods and storms, it points to a need for further data balancing techniques like SMOTE to mitigate bias in modeling efforts.

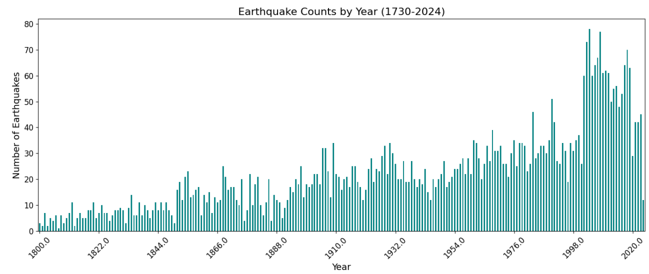

Figure 7: Earthquake Counts by Year

Disaster Type Distribution: The dataset exhibited a highly skewed distribution of disaster types, with floods (`4110 events`) and storms (`2607 events`) dominating. A positive skewness of `2.76` indicated a strong bias towards frequent disaster types, which could impact model training if not addressed. We used SMOTE to remove skewness

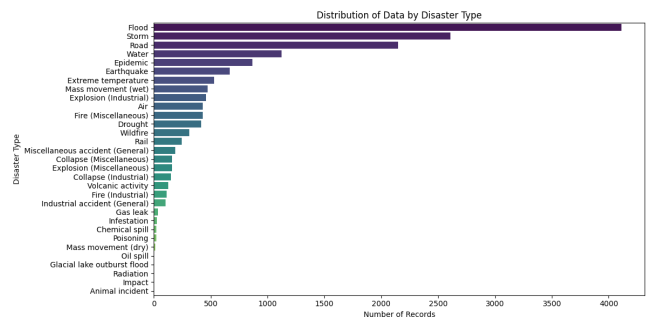

Figure 6: Disaster Type Distribution

Earthquake Data Analysis. An analysis of earthquake data provided insights into the distribution and impact of earthquakes:

- **Magnitude Distribution**: A histogram of earthquake magnitudes showed a normal distribution, with most earthquakes having a magnitude between 4 and 6.
- **Geospatial Distribution**: A scatter plot revealed that earthquake occurrences were spread across the globe, with clusters in regions like the Pacific Ring of Fire and areas near tectonic plate boundaries.
- **Magnitude vs. Damage**: A scatter plot of earthquake magnitudes against total damage showed a positive correlation, where larger earthquakes tend to cause more significant damage.

  Key Insights**:**
  - Earthquakes in regions with active tectonic plates, like the Pacific coast, have a higher magnitude and cause more damage.
  - There is a strong relationship between earthquake magnitude and the total economic damage.

4.3.2 Insights from EDA.

- **Skewness in Disaster Types:** The overrepresentation of certain disaster types necessitates the use of resampling techniques or specialized loss functions to train balanced models effectively.

- **Temporal and Geographic Trends:** Seasonal patterns and region-specific disparities in disaster occurrences were observed, aiding feature selection and time series modeling.
- **Regional Disparities:** Certain regions showed disproportionately high frequencies and severities, underlining the importance of regional adjustments in model predictions.

These findings laid the groundwork for the subsequent stages of data preprocessing, feature engineering, and model development, ensuring that the predictions are robust and actionable.

Tsunami Data Visualization. For the **Tsunami** data, similar steps were followed to identify regions prone to tsunamis and their impact. The dataset provided information on earthquake magnitude, depth, and tsunami occurrences, which were used to identify any correlations.

- **Tsunami Frequency**: The analysis of **Tsunami occurrences** showed that tsunami events were closely associated with high-magnitude earthquakes, especially those occurring under the ocean, which are more likely to trigger large tsunamis.
- **Magnitude vs. Tsunami Occurrence**: Visualizations, including scatter plots and heatmaps, were used to analyze the relationship between earthquake magnitude and tsunami occurrences. The data revealed that larger magnitude earthquakes, particularly those above magnitude 7, had a higher likelihood of generating tsunamis.

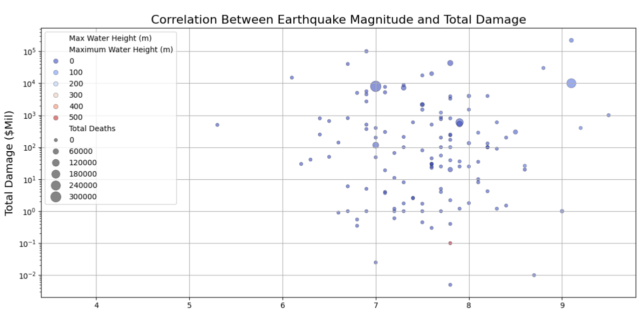

Figure 8: Correlation Between Earthquake Magnitude and Total Damage

The EDA performed on the disaster and earthquake datasets provided valuable insights into the global patterns of natural disasters, including frequency, severity, and geographical distribution. The analysis showed that floods and storms are the most common disasters, while regions near tectonic plate boundaries are more prone to earthquakes and tsunamis. The aid contributions data highlighted the countries leading in disaster relief efforts, and skewness was observed in the distribution of disaster types, suggesting the need for advanced techniques like SMOTE to balance the data for further analysis.

4.4 Modeling Approaches:

The predictive models have been built using a combination of time series models and machine learning techniques. We have explored the following approaches:

4.4.1 Clustering. The project began with preprocessing the historical disaster dataset, including cleaning, handling missing data, and normalizing variables. To quantify disaster severity, a severity metric was created using three key features: 'Total Deaths', 'No. Injured', and 'Total Damage ('000 US$)'. This metric was calculated with the formula:

$$\begin{aligned} \text{severity\_metric} &= (\text{Total Deaths} \times 2) && (1)\\ &+ (\text{No. Injured} \times 0.75) && (2)\\ &+ \text{Total Damage ('000 US\$)} && (3) \end{aligned}$$

The weights were chosen based on the relative significance of each factor, with fatalities being given the highest importance, followed by economic damages and injuries. Multiple feature combinations were tested, but these three features provided the most meaningful clustering results.

After deriving the severity metric, K-means clustering was applied, yielding a Silhouette Score of over 90%, which indicated highly compact and meaningful clusters. The clustering labels generated by K-means enabled the categorization of disasters based on severity, providing a foundational dataset for subsequent supervised learning tasks. In contrast, DBSCAN and agglomerative clustering were also tested but produced poor Silhouette Scores, largely due to their sensitivity to parameters and challenges in handling high-dimensional data. As a result, these methods were excluded. The results of K-means clustering highlighted the utility of unsupervised learning in grouping disasters with similar characteristics and provided a robust basis for analyzing disaster severities.

4.4.2 Supervised Learning for Severity Prediction. Following clustering, the labeled dataset was used to train supervised machine learning models for predicting disaster severity. Key features, including 'Total Deaths', 'No. Injured', and 'Total Damage ('000 US$)', were used as inputs. Initially, several combinations of hyperparameters and models were explored to optimize performance. The ensemble stacking model, which combines Random Forest, Gradient Boosting, and a meta-model of Logistic Regression, achieved the best results. Hyperparameters such as 'n_estimators' were fine-tuned, with 100 being chosen as the optimal value for both Random Forest and Gradient Boosting based on the dataset.

During the initial iterations, the stacking model struggled to accurately predict the minority severity class due to class imbalance. This was resolved by adding the 'class_weight=balanced' argument to both the Random Forest and Logistic Regression models, ensuring that the less frequent severity labels received appropriate attention. This adjustment significantly improved the model's performance. The stacking model achieved over 90% accuracy during training and yielded testing accuracies of 80% for earthquake data and 73% for tsunami data. These testing accuracies were obtained by comparing the predictions of the stacking model against the severity labels generated during the clustering phase, demonstrating the robustness and reliability of the supervised learning approach.

4.4.3 Time Series Analysis. Time series analysis was conducted to visualize trends in disaster severity over time for earthquakes and tsunamis. Using the predicted severity labels from the clustering and supervised learning phases, the average severity for each time period was calculated. This average was plotted against time to create time series graphs for both earthquake and tsunami data. The results revealed a general increasing trend in disaster severity over time, consistent with the growing intensity and frequency of natural disasters driven by factors such as climate change, urbanization, and population growth. These trends emphasize the importance of adaptive disaster management strategies and proactive resource allocation to mitigate the escalating impacts of such events. The visualizations provided a clear understanding of how disaster severity has evolved over time, offering critical insights for future disaster preparedness and response strategies.

4.4.4 Analysis of Financial Aid Gaps. An important component of this project has been the analysis of regions or disaster events with high severity but inadequate financial aid. By cross-referencing predicted severity with financial aid data, we have aimed to identify areas where government or humanitarian intervention is lacking. This analysis has helped policymakers ensure that vulnerable regions have received adequate resources to recover from disasters.

5 EVALUATION

The evaluation of the proposed disaster severity prediction system will focus on the performance of both the clustering and supervised learning models. This section outlines the metrics, validation techniques, and real-world testing methods used to assess the system.

5.1 Model Performance Evaluation:

5.1.1 Clustering Model: The clustering phase utilized K-means to categorize disasters based on the severity metric derived from the features *Total Deaths*, *No. Injured*, and *Total Damage ('000 US$)*. The clustering achieved a Silhouette Score of over **90%**, indicating well-defined and meaningful clusters. While alternative methods such as DBSCAN and Agglomerative Clustering were explored, they produced subpar Silhouette Scores due to their sensitivity to hyperparameters and difficulties in handling the high-dimensional nature of the dataset.

The high-quality clusters generated by K-means provided severity labels that served as inputs for the supervised learning models. This step established a solid foundation for subsequent tasks by grouping disasters with similar severity characteristics.

5.1.2 Supervised Models: The severity labels obtained from clustering were used to train supervised machine learning models for severity prediction. A stacking ensemble model was employed, combining Random Forest and Gradient Boosting as base learners, with Logistic Regression serving as the meta-model. To optimize performance, hyperparameters such as *n_estimators* were tuned, with 100 providing the best balance of accuracy and efficiency.

```
Earthquake Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.59      0.74      3292
           1       0.70      1.00      0.82      3152

    accuracy                           0.79      6444
   macro avg       0.85      0.80      0.78      6444
weighted avg       0.85      0.79      0.78      6444

Tsunami Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.47      0.64      1476
           1       0.64      1.00      0.78      1404

    accuracy                           0.73      2880
   macro avg       0.82      0.74      0.71      2880
weighted avg       0.83      0.73      0.71      2880

Accuracy of Earthquake Model:  0.7906579764121664
Accuracy of Tsunami Model:  0.7302083333333333
```

Figure 9: Stacking Results

Initially, the stacking model exhibited poor performance on the minority class due to class imbalance. This issue was mitigated by applying **class_weight='balanced'** to Random Forest and Logistic Regression, ensuring that both majority and minority severity classes received equal attention. These changes significantly improved performance. The stacking model achieved the following testing accuracies:

- **80%** on earthquake data.
- **73%** on tsunami data.

These results were validated by comparing the model's predictions against the severity labels generated during clustering, highlighting its robustness and ability to generalize across datasets.

5.1.3 Time Series Analysis: The time series analysis visualized trends in disaster severity over time for earthquakes and tsunamis. Using the predicted severity labels, the average severity was calculated for each time period and plotted to create time series graphs. The results revealed a clear **increasing trend** in disaster severity over time. This trend aligns with global factors such as climate change, urbanization, and population growth, which contribute to the rising frequency and intensity of natural disasters.

The time series graphs provided valuable insights into the temporal evolution of disaster severity, underscoring the need for proactive and adaptive disaster management strategies. These visualizations serve as a critical tool for identifying patterns and supporting future preparedness efforts.

5.1.4 Analysis of Financial Aid Gaps. The analysis of financial aid gaps was performed by cross-referencing predicted severity levels with available financial aid data. This analysis identified regions and disaster events with high severity but inadequate aid, highlighting areas requiring greater intervention from governments and humanitarian organizations. By pinpointing these gaps, the project

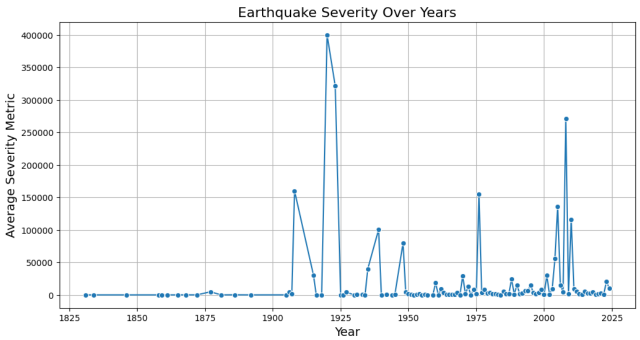

Figure 10: Earthquake Severity Over Years

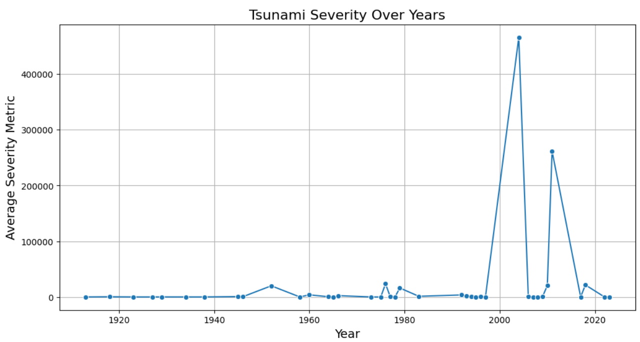

Figure 11: Tsunami Severity Over Years

aims to assist policymakers in ensuring equitable resource distribution and improving recovery efforts for the most vulnerable regions.

By focusing on a variety of performance metrics and validation techniques, this evaluation process provides a comprehensive assessment of the models' effectiveness in disaster severity prediction. The clustering phase, validated with a Silhouette Score of over 90%, demonstrated the ability to group disasters with similar characteristics accurately. The supervised stacking model, optimized through hyperparameter tuning and addressing class imbalance, achieved robust testing accuracies of 80% on earthquake data and 73% on tsunami data, showcasing its reliability in predicting severity levels across datasets. The time series analysis revealed a clear increasing trend in disaster severity over time, providing critical insights into the evolving nature of disaster impacts. Additionally, the analysis of financial aid gaps highlighted regions with high severity but inadequate support, emphasizing the system's real-world applicability in guiding resource allocation and improving disaster response strategies.

6 DISCUSSION

Throughout this project, several lessons were learned that provided valuable insights into disaster severity modeling. One key lesson was the importance of robust data preprocessing, including cleaning, handling missing values, and feature selection, as these steps were crucial for achieving reliable clustering and supervised learning results. The creation of a well-designed severity metric using weighted features allowed for more meaningful clustering and improved the interpretability of the results.

What worked particularly well was the use of K-means clustering, which yielded a Silhouette Score of over 90%, successfully grouping disasters into well-defined severity categories. Additionally, the stacking ensemble model performed robustly, achieving testing accuracies of 80% for earthquake data and 73% for tsunami data. The use of class-weight adjustments resolved the imbalance issue in the supervised learning phase, ensuring better recognition of minority classes.

However, certain challenges arose during the project. Alternative clustering methods like DBSCAN and agglomerative clustering struggled to produce meaningful clusters due to parameter sensitivity and the high-dimensional nature of the data. Similarly, addressing class imbalance required careful tuning, as initial iterations of the stacking model failed to predict the minority class effectively. Another limitation was the exclusion of predictive time series models like ARIMA due to the scope of the study, though time series visualization still provided critical insights into increasing disaster severity trends.

Future work can address these limitations by exploring advanced clustering techniques, such as hierarchical clustering with adaptive parameters, or deep learning models like autoencoders for unsupervised learning. For supervised learning, further improvements can be made by experimenting with deep ensemble models or neural networks to enhance prediction accuracy. Scaling the model by training the stacking ensemble on larger datasets and testing it on additional disaster types will help improve classification accuracy and provide deeper insights into the model's performance across diverse scenarios. Building a user-friendly dashboard is another critical direction, enabling users to interact with the system through real-time updates and customizable features such as filtering by disaster type or location. Such a platform would make the system more accessible for decision-makers and further enhance its practical value for disaster preparedness and risk management.

7 CONCLUSION

This project successfully demonstrated a robust framework for disaster severity modeling by integrating clustering, supervised learning, and time series visualization techniques. The key tasks included preprocessing historical disaster datasets, developing a severity metric, and applying K-means clustering to categorize disaster events. The clustering phase achieved a Silhouette Score of over 90%, ensuring meaningful and well-separated severity groups.

Supervised learning models were trained using the labeled data generated from clustering, with the stacking ensemble model delivering strong results. The model achieved testing accuracies of 80% on earthquake data and 73% on tsunami data, after addressing class imbalance and tuning key hyperparameters. Time series analysis further revealed an increasing trend in disaster severity over time, underscoring the growing impact of natural disasters due to climate change, urbanization, and population growth.

Additionally, the analysis of financial aid gaps provided actionable insights by identifying regions with high severity but inadequate support, emphasizing the practical value of this framework. Overall, the project highlights the potential of machine learning and temporal analysis for improving disaster preparedness and resource allocation, laying the groundwork for further advancements in disaster risk management.

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9 APPENDIX

9.1 Honor Code Pledge

We affirm that this work adheres to the highest standards of academic integrity and originality. All tasks were completed collaboratively, ensuring equal contribution and effort from all team members.

Every member worked on all the presentations and reports with equal contribution.

9.2 Individual Contribution

Team Members:

- Abdul Rafay Ahmed Khan
- Aniket Singh
- Mohit Gupta
- Samiksha Patil

9.2.1 Abdul Rafay Ahmed Khan. Contributed in data cleaning and machine learning

9.2.2 Aniket Singh. Contributed in statistical analysis and data visualizations

9.2.3 Mohit Gupta. Contributed in data cleaning and machine learning

9.2.4 Samiksha Patil. Contributed in statistical analysis and data visualizations