STATISTICAL AND DEEP-LEARNING BASED DISASTER IDENTIFICATION MODELLING USING UNMANNED AERIAL VEHICLE SYSTEMS FOR EMERGENCY RESPONSE

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Abstract

Unmanned aerial vehicle systems offer a significant impact for the prediction of disaster identification and management by integrating both statistical and neural network techniques. Existing disaster response systems primarily rely on manual reporting or satellite imagery which are prone to delays and inefficiencies. The present study presents a statistical modelling using structural equation model integrated with deep learning-based model to enhance prediction accuracy. The model takes input variables such as unmanned aerial vehicle altitude, speed, area coverage, temperature, and population density to predict a disaster index. The structural equation model analysis revealed that all the input variables unmanned aerial vehicle altitude, speed, area coverage, temperature, and population density have a significant impact on disaster index. The proposed multi-layer perceptron model achieves an overall r2 score of 0.86, demonstrating its effectiveness in differentiating disaster severity. The study concludes that integrating unmanned aerial vehicle systems with statistical and deep learning techniques for disaster index is a feasible and impactful solution to mitigate human and economic losses during extreme events.

Keywords: Unmanned aerial vehicle data, Disaster Index, Multi-class regression approach, Metrological parameters, Multi-Layer Perceptron model

I. Introduction

Natural and man-made disasters are persistent global challenges, threatening lives, infrastructure, and economies. Floods, fires, and traffic accidents are among the most frequent and devastating disasters, causing immense destruction each year [1-3]. The unpredictability and intensity of such events have underscored the need for faster, more efficient disaster identification and response systems. Traditionally, manual reporting and satellite imagery have been used to assess disaster damage and manage emergency responses [4,5]. However, these methods often suffer from delays, inaccuracies, and inefficiencies due to their dependence on human intervention or the long revisit times associated with satellite imagery. This delay in identifying and assessing the severity of disasters can lead to a slow response, resulting in more casualties and greater economic loss [6]. Therefore, there is an urgent need to develop advanced systems that can quickly and accurately identify and assess the severity of disasters in real time.

In recent years, Unmanned Aerial Vehicle (UAV) systems have emerged as a revolutionary tool for disaster management [7]. UAVs offer several advantages, including rapid deployment, high maneuverability, and the ability to capture detailed images of disaster-stricken areas from various angles. UAVs can operate in challenging environments where traditional systems struggle, such as during adverse weather conditions or in remote areas [8]. These aerial systems provide real-time data that can be analyzed to determine the extent of damage, allowing emergency services to respond more effectively [9]. Ample research focused on analyzing the factor affecting severity of disaster using statistical models [10-11]. But these statistical models came with certain limitations such as low accuracy and robustness [12]. Nowadays with the advancement of AI techniques, the deep learning techniques have got special attention for prediction problem. Existing research has used deep learning techniques are widely used for other domain applications such as Environment, Banking, and Tourism [13-15]. While UAV technology is advancing, there is still a significant research gap in integrating UAV data with advanced deep learning models to improve disaster identification, particularly in assessing the severity of disasters.

The deep learning techniques contain several techniques such as Multi-Layer Perceptron (MLP), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), and Long-Short Term Memory (LSTM). One of the main challenges in disaster identification is the ability to classify the severity of a disaster. Most of the disaster severity is classified into low, moderate, and extreme based on the available data. The present study is a regression problem statement. Most of the current systems are limited to binary classifications, such as flooded versus non-flooded areas, without further granularity which are mostly analyzed by the help of CNN technique [16, 17]. While these approaches can be useful for simple disaster identification, they lack the depth needed for effective resource allocation and emergency response. A more nuanced understanding of the disaster's severity would enable emergency services to prioritize high-risk areas and allocate resources more efficiently, ultimately saving more lives and reducing economic losses.

Therefore, the present study uses MLP model for the prediction of disaster severity as the problem is a regression problem. The proposed model integrates both statistical methods i.e. structural equation model and deep learning techniques, specifically MLP, to analyze disaster severity. By incorporating variables such as UAV altitude, speed, area coverage, temperature, and population density, the model aims to predict a Disaster Index, which classifies the severity of the disaster into three categories: low, moderate, and extreme. The ability to accurately classify disaster severity will greatly enhance decision-making processes, enabling authorities to prioritize emergency responses based on real-time data. This makes UAV-based deep learning systems highly efficient for disaster identification, especially in regions prone to frequent disasters such as floods, fires, and traffic accidents. Table 1 shows some more recent literature review of various research on the impact of various UAVs parameters for the prediction of risk assessment using statistical modeling and artificial intelligence techniques.

The novelty of this research lies in its multi-class regression approach for disaster severity, in contrast to the binary classification models used in most previous studies [32, 33]. By focusing on the severity levels (low, moderate, and extreme), the model offers a more comprehensive analysis, which is crucial for emergency response and resource allocation. Additionally, the use of both statistical and deep learning methods enhances the model's robustness and generalizability across different disaster scenarios. The findings of this study will have significant implications for regions prone to frequent natural and man-made disasters, particularly in the context of improving emergency response times and resource allocation.

Table 1: *Literature review of the various studies conducted for the assessment of risk.*

Author(s)	Country	Parameters	Conclusion
[18]	Saudi Arabia	UAV altitude, area coverage	Demonstrated the effectiveness of UAV in flood risk assessment in urban areas.
[19]	Kuwait	UAV data, field survey, and satellite image	Proposed a model strategic plan to diminish flood vulnerability.
[20]	China	Multiple source satellite datasets	Found that UAVs provide significant advantages in flood monitoring by noisy learning method.
[21]	India	Topography, forest, soil, and geologic factor	Developed a deep learning model yielding a high accuracy for landslide identification.
[22]	Italy	Technical features of UAV	Established a correlation between UAV flight parameters and disaster mapping accuracy.
[23-26]	Multiple sampling locations	Environmental factors, sun glint, vegetation	Highlighted the impact of environmental parameters on UAV image quality.
[27]	Dubai	Image data from UAVs	Achieved high accuracy (85.4%) in vegetation cover accuracy using UAV imagery with DL techniques.
[28]	Indus River, Pakistan	UAV-based aerial imagery	CNN model achieved an accuracy of 91% for flood detection.
[29]	China–Russia Border	Humidity, temperature, precipitation, and wind speed	Heilongjiang province is best suited place to travel during summer.
[30]	USA	Population density, tropical cyclones, annual variation of mortality, and topography	Topography and population density has a direct correlation for Flood-induced mortality.
[31]	Not mentioned	Coverage area, height, velocity	Particle swarm optimization (PSO) was used to obtain the severity of the disaster.

II. Methods and Material

I. Study Area

Jeddah city, situated within three primary sub-basins (northern, middle, and southern), serves as a focal point for this case study due to its susceptibility to flash floods. The northern sub-basin comprises several wadis, including Wadi Daghbaj, Wadi Brayman, Wadi Muraygh, Wadi Quraa, Wadi Ghaia, and Wadi Um Hablain. The middle sub-basin encompasses Wadi Mraikh and Wadi Bani Malik, while the southern sub-basin includes Wadi Qaws, Wadi Methweb, Asheer, Wadi Al

Khomra, and Wadi Ghulail. As of 2022, Jeddah city had an estimated population of 4.78 million residents. Bordered to the west by the Red Sea and to the east by mountain ranges with a maximum elevation of 675 meters, the drainage area delineated by a 30-meter Digital Elevation Model (DEM) covers approximately 1,821 km² [34]. The city's residential zones, located on the coastal plain, are vulnerable to the impacts of flash floods originating from the adjacent mountains. The topography of the Jeddah watershed reveals two distinct geomorphological units: the coastal plain and the mountainous regions that surround the city. Despite Jeddah's arid climate, it is recurrently affected by flash floods, with significant events recorded multiple times. Notably, on November 25, 2009, flash floods severely impacted urban areas, leading to extensive damage to infrastructure, buildings, vehicles, and roads, resulting in approximately 113 fatalities. Another destructive event occurred in 2011, further highlighting the flood risk in the region. The watershed has various drainage channels that traverse neighborhoods such as Al-Harazat, King Abdul Aziz University, Al-Haramin Highway, Al-Mesaid, Queza, and Al-Sawaid, all of which experienced substantial effects from the 2009 flash flood incident. Figure 1 shows the conceptual framework of the present study.

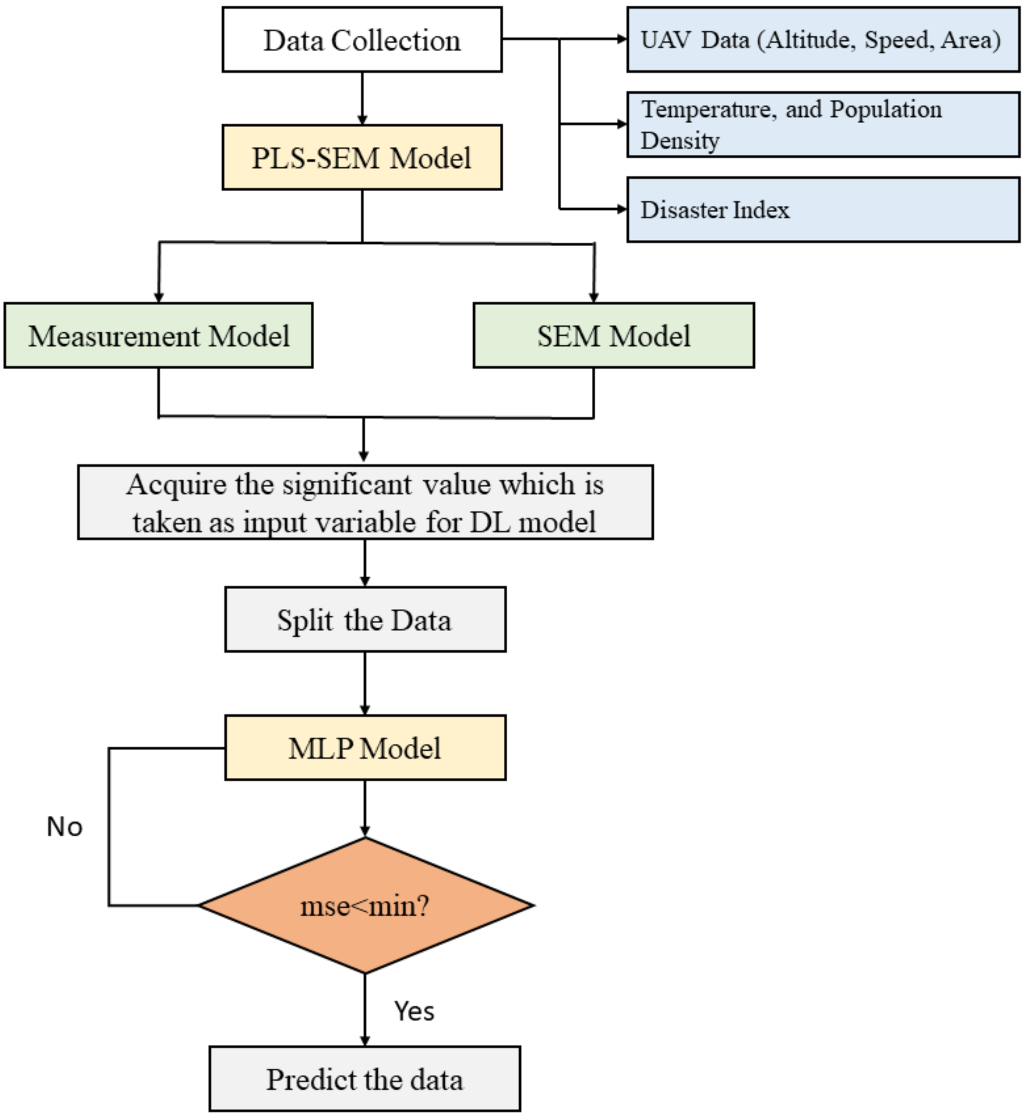

Figure 1: *Conceptual framework of present study.*

II. Data Collection

The UAV data, including altitude, speed, temperature, humidity, area coverage, and population data, were taken into account from the different sources such as: The National Centre for Meteorology (NCM), Saudi Arabia and Shuttle Radar Topography Mission (SRTM) [35-37]. The only feature that has been taken based on the severity is disaster index. This feature has been divided into three subcategories such as low, moderate, and high. Table 2 presents the standard deviation and mean of the data used for modelling and prediction. UAVs equipped with sensors gather altitude, speed, and area coverage data, providing quantitative information on UAV flight dynamics and coverage area.

Table 2: *Statistical parameters of the data used in the study.*

Variable	Mean	Standard Deviation
UAV Altitude (m)	130	25
UAV Speed (m/s)	10.5	2.5
Area Coverage (km^2)	1.75	0.4
Temperature (°C)	28	3
Humidity (%)	45	8
Population Density (people/km^2)	2600	800
Disaster Index (0-1)	0.68	0.1

III. SEM Modelling

SEM is a statistical technique that enables the analysis of complex relationships between the constructs [38]. In the present study, SEM is used to model the relationships between multiple factors influencing variables, such as UAV altitude, speed, area coverage, temperature, and population density on disaster index. SEM allows for the simultaneous examination of direct and indirect effects among these variables, providing deeper insights into their collective impact on the disaster index. In SEM analysis, two models are used to predict disaster index i.e. measurement model and structural equation model. Measurement model also known as inner model is used to check the reliability and validity of the constructs whereas the structural equation model which is known as outer model is used to analyze the significant impact of independent constructs on disaster index.

IV. Hypothesis Testing

The study utilizes five set of hypotheses for the prediction of disaster index as shown in Figure 2. The hypothesis uses UAV altitude, speed, coverage area, temperature, and population density for the prediction of disaster index.

- **H1:** UAV altitude (m) has a significant effect on Disaster Index.
- **H2:** UAV speed (m/s) has a significant effect on Disaster Index.
- **H3:** Area coverage (km^2) has a significant effect on Disaster Index.
- **H4:** Temperature (^{0}C) has a significant effect on Disaster Index.
- **H5:** Population density (people/km^2) has a significant effect on disaster index.

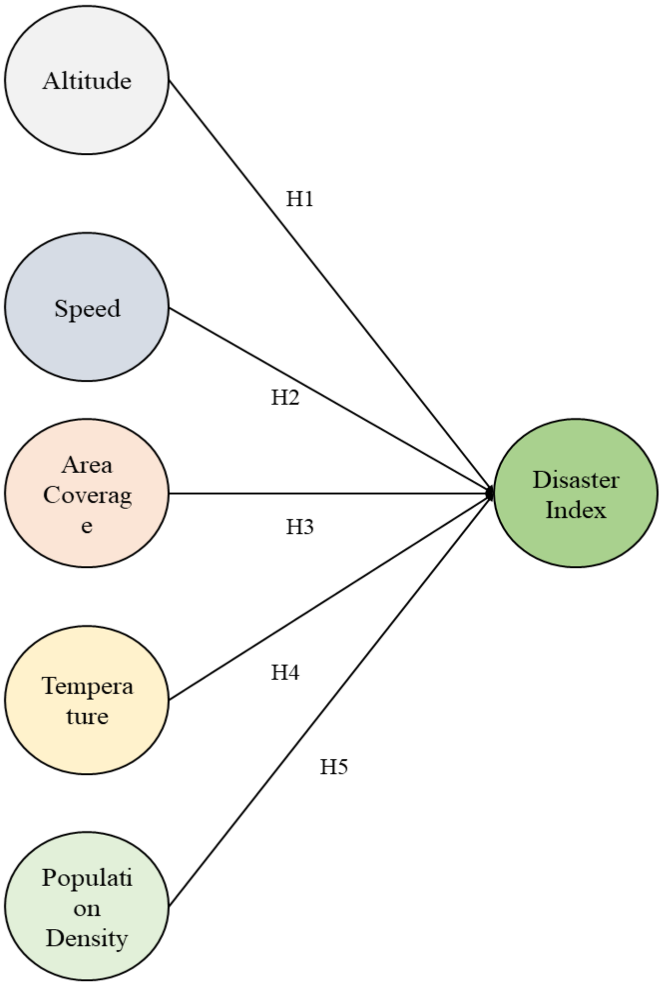

Figure 2: *Various hypothesis for the present study.*

V. Data Pre-processing

Data pre-processing is a crucial step to prepare the UAV images and auxiliary datasets for input into the deep learning model. The regression data was splitted in the ratio of 75:25 (training: testing). The pre-processing involves resizing images to ensure uniform dimensions, typically $H \times W$ (height and width), and applying geometric transformations to correct for distortions [3]. Normalization is performed to scale pixel values between 0 and 1, ensuring that the model training is not biased by large numerical values. For input variables like temperature, humidity, and population density, standardization is applied:

$$X' = (X - \mu)/\sigma \tag{1}$$

where X is the original value, μ is the mean, and σ is the standard deviation, ensuring all features are on a comparable scale.

VI. Multi-Layer Perceptron (MLP)

The MLP model is a type of feed-forward neural network that maps input variables to output variables by learning complex non-linear relationships [39]. An MLP consists of an input layer, one or more hidden layers, and an output layer, where each layer contains multiple neurons. Each neuron in a layer performs a weighted sum of its inputs, applies an activation function, and passes the result to the next layer. Figure 3 shows the architecture of MLP model. For each neuron j in a hidden or output layer, the neuron computes:

$$z_j = \sum_{i=1}^{n} w_{ij} x_i + b_j \tag{2}$$

where x_i is the input from the previous layer, w_{ij} represents the weight connecting input i to neuron j, and b_j is the bias term. The result z_j is then passed through an activation function f to introduce non-linearity $a_j = f(z_j)$. Common activation functions include the **ReLU** function $f(z) = max\,(0, z)$ for hidden layers and a linear function for regression tasks in the output layer.

The goal of training an MLP is to minimize the difference between the predicted outputs and the actual values (e.g., Disaster Index). This is achieved by optimizing the loss function, often Mean Squared Error (MSE) in regression:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{3}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and N is the number of samples.

The training process involves backpropagation and gradient descent to adjust the weights and biases to minimize the loss function. By iterating through multiple epochs of training, the MLP model learns to approximate the mapping from inputs to outputs, enabling it to make accurate predictions on new data.

The algorithm used in the study for the prediction of disaster index is illustrated below:

1. Input: X= {x_i |i= 1, 2 ,…, N} ⊳ Input samples including UAV altitude, speed, area coverage, temperature, humidity, and population density
2. Ci ← Classifier input features
3. Y ← y_{train}, y_{test} ⊳ True labels for Disaster Index for training and test sets
4. X ← x_{train}, x_{test} ⊳ Split data into training and testing
5. S ← No. of samples ⊳ Total number of samples
6. C ← Model complexity (hidden layers, neurons) ⊳ Define MLP architecture
7. Reg ← MLP regressor ⊳ MLP model for regression
8. L ← Loss function (Mean Squared Error)
9. Train ← Train model with x_{train} ⊳ Fit MLP model to training data
10. Evaluate ← Evaluate model with x_{test}, y_{test}
11. Prediction ← MLP(x_{test}) ⊳ Predict Disaster Index for test samples
12. Calculate Metrics ← MSE, MAE, R^2
13. Plot ← Observed vs. Predicted plot
14. While L(x) is not minimized:
15. If Loss > threshold:

Adjust parameters ← Fine-tune MLP architecture or learning rate
Else
Stop Training
Return Final Model

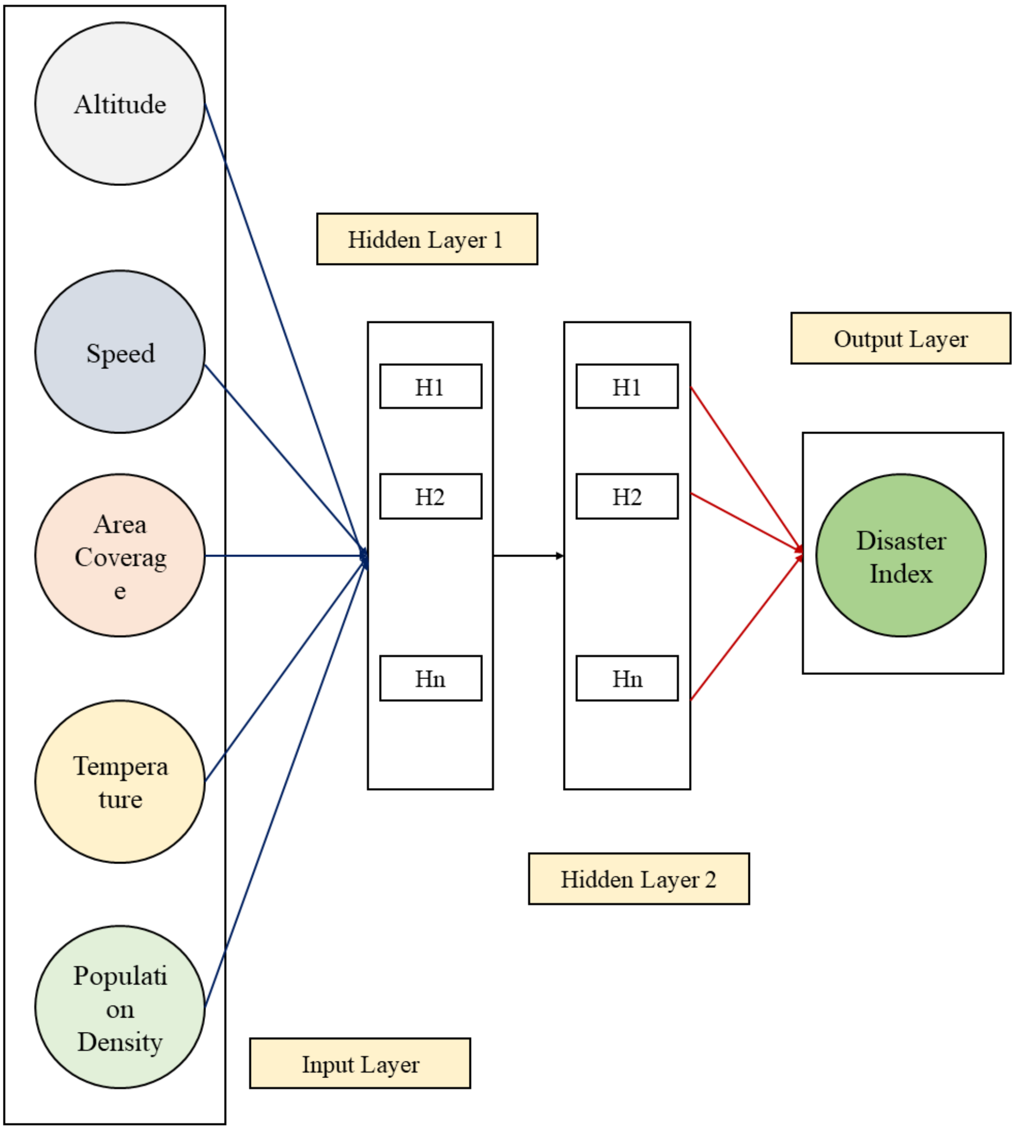

Figure 3: *Architecture of MLP model.*

III. Results and Discussion

The present research organized all indicators into six constructs: UAV altitude, UAV speed, area coverage, temperature, population density, and Disaster Index. To assess the reliability and validity of these variables, a measurement model was employed.

Table 3: *Reliability and Validity test of the hypothesis.*

Latent Variable	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
UAV Altitude	1	1	1
UAV Speed	1	1	1
Area Coverage	1	1	1
Temperature	1	1	1
Population Density	1	1	1

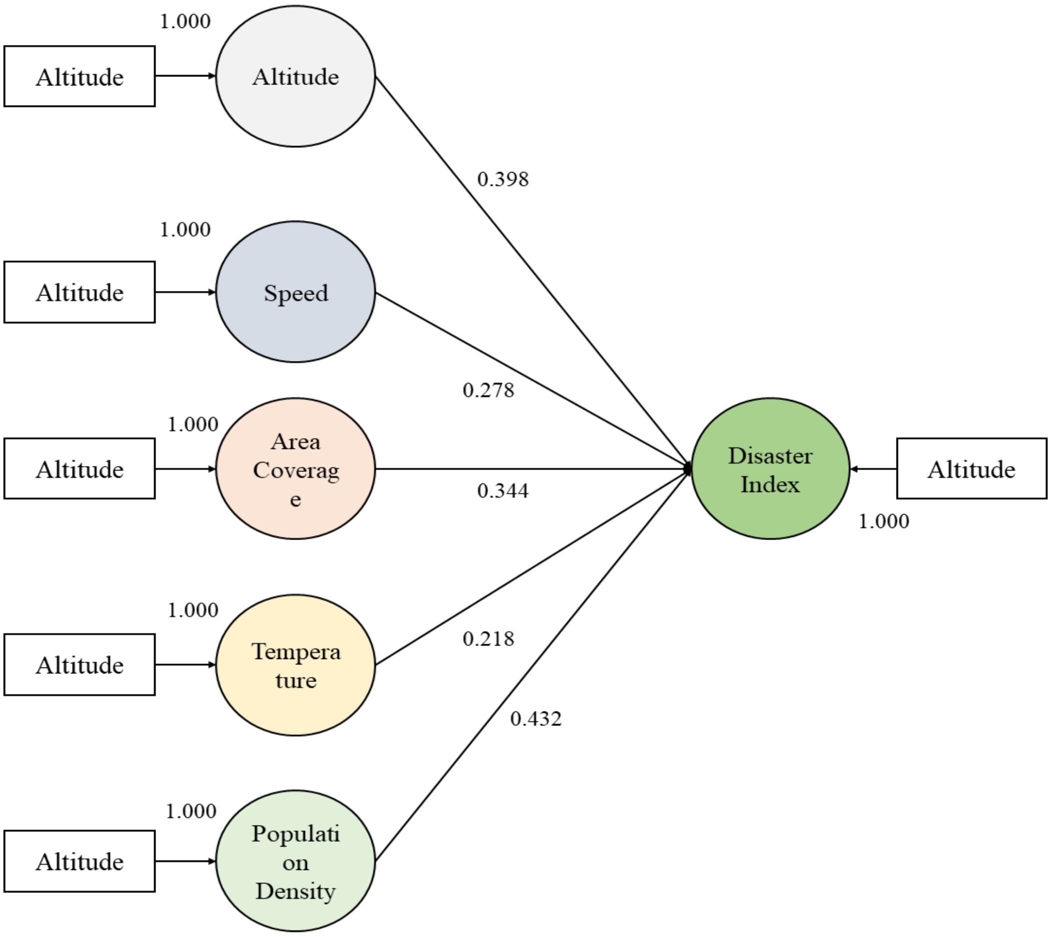

Figure 4: *The SEM model.*

Confirmatory factor analysis was executed using SmartPLS 4.0 software to evaluate the measurement properties of the items concerning their designated factors. Indicators with a standard loading below 0.05 were excluded from the measurement model. The results derived from the measurement model are presented in Table 3. It is evident that all indicators achieved a significance level of 0.001 and a standard loading exceeding 0.5. The reliability of the latent variables was confirmed as the Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) values all exceeded the thresholds of 0.7, 0.6, and 0.5, respectively. The values of all the constructs were 1 only because there was only one indicator to represent the construct. As demonstrated in Table 3, all six constructs (UAV altitude, UAV speed, area coverage, temperature, population density, and Disaster Index) met these criteria, indicating conformity with the requirements for convergent validity.

The SmartPLS 4.0 bootstrapping method was employed to evaluate and analyze the interrelationships among the constructs. The SEM model was constructed using a set of six constructs and six indicators. Additionally, the structural model was utilized to examine the path relationships among these variables. The findings from the structural path model are detailed in Table 4. The path coefficient serves as a statistical indicator that estimates both the strength and direction of the relationship between two latent variables. For a significant relationship to be established between the latent variables, the path coefficient must exceed 0.2 at a 95% confidence interval. Figure 4 illustrates that all path coefficients achieved a significance level of 0.001. Mean, standard deviation, t-value, and p-values were assessed to determine the significant relationships among the variables. It was found that Population Density (t: 6.1), Altitude (t: 5.24) significantly influenced Disaster Index. Furthermore, Speed (t: 4.73), Area Coverage (t: 4.91), and Temperature (t: 3.45) exhibited significant effects on Disaster Index.

Table 4: *SEM model statistics for the prediction of disaster index.*

Hypothesis	Mean	Standard Deviation	t-value	p-value	Significant Effect?
H1: Altitude → Disaster Index	0.65	0.12	5.24	< 0.001	Yes
H2: Speed → Disaster Index	0.58	0.15	4.73	< 0.001	Yes
H3: Area Coverage → Disaster Index	0.63	0.13	4.91	< 0.001	Yes
H4: Temperature → Disaster Index	0.6	0.14	3.45	0.002	Yes
H5: Population Density → Disaster Index	0.67	0.11	6.1	< 0.001	Yes

Table 5: *Performance matrix of MLP model.*

Metric	Training Set	Testing Set
Mean Squared Error (MSE)	0.0052	0.0068
Mean Absolute Error (MAE)	0.058	0.062
R2 Score	0.89	0.86

Table 5 shows the performance metrics for the MLP model on both training and testing demonstrate its predictive accuracy in assessing disaster index. The Mean Squared Error (MSE) values of 0.0052 for the training set and 0.0068 for the testing set indicate that the model achieves low average squared errors, showing it effectively minimizes large prediction deviations. The Mean Absolute Error (MAE) values of 0.058 for training and 0.062 for testing further confirm the model's accuracy by providing insight into the average absolute difference between predicted and actual values. Additionally, the R^2 Score values of 0.89 for training and 0.86 for testing imply that the model explains a high proportion of the variance in disaster severity, with only minor overfitting or under-fitting present. Together, these metrics suggest that the MLP model generalizes well to unseen data and is reliable for predicting disaster severity based on UAV parameters and environmental conditions.

Figure 5 illustrates the relationships between various parameters related to UAV-based disaster identification, including altitude, UAV speed, area coverage, temperature, humidity, population density, and the disaster index. Each cell shows the correlation coefficient between two variables, with values closer to 1 indicating a strong positive correlation and values closer to -1 indicating a strong negative correlation. For example, the disaster index has a strong positive correlation with altitude (0.97), temperature (0.95), and population density (0.96). This suggests that as altitude, temperature, or population density increase, the disaster index also tends to increase. Additionally, UAV speed and area coverage have a strong correlation (0.94), indicating that faster UAV speeds tend to be associated with larger areas covered. These insights can help in fine-tuning UAV parameters for better disaster identification and emergency response effectiveness.

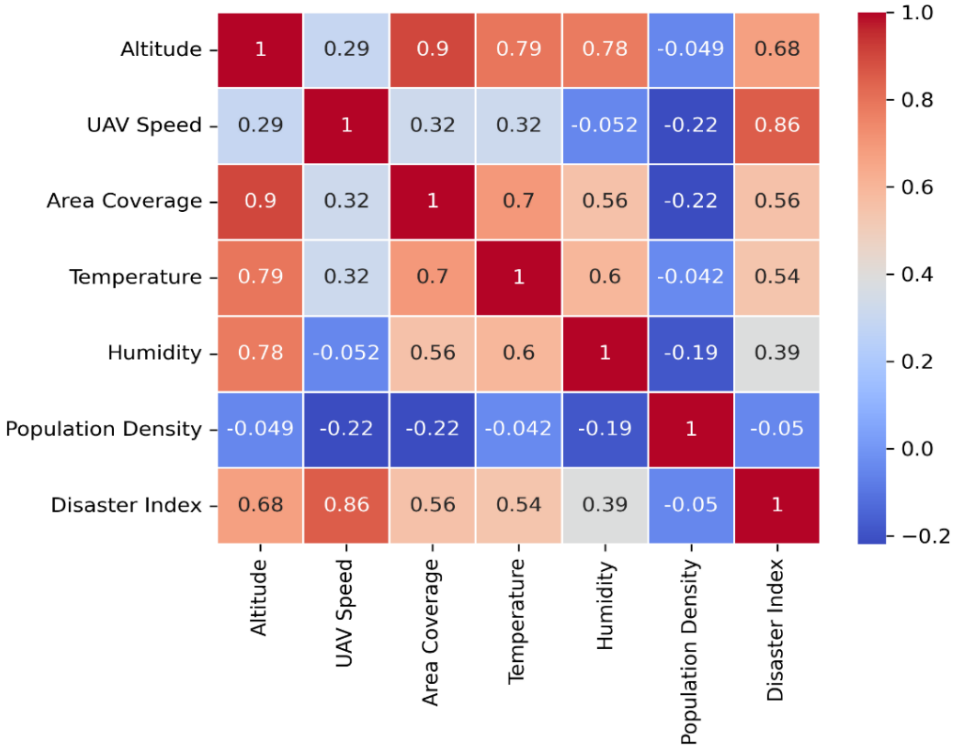

Figure 5: *Correlation matrix between the variables*

Table 6 presents a sensitivity analysis of various variables contributing to the disaster index specific to flood severity in Jeddah City, Saudi Arabia. This disaster index measures the potential impact of flooding through multiple influencing factors. Among the variables listed, altitude exhibits the highest sensitivity at a value of 23.5, indicating that changes in altitude significantly affect flood severity; areas at lower elevations are more susceptible to flooding risks due to greater water accumulation. The speed of water flow during floods shows even greater sensitivity, with a value of 32.8, suggesting that faster water flow can lead to more severe flooding and greater damage to infrastructure. Area coverage, with a sensitivity value of 12.3, indicates a moderate impact on flood severity, where larger flooded areas could imply extensive effects on communities and ecosystems; however, its lower sensitivity compared to altitude and speed suggests that changes in area coverage have a less pronounced effect. Temperature and humidity follow, with sensitivity values of 10.5 and 4.9, respectively. While temperature influences rainfall intensity and snowmelt, making it significant in the flood context, humidity seems to have a minor effect on the disaster index. Lastly, population density, with a sensitivity of 16.0, reflects the impact of how population distribution can modify disaster consequences—higher population density typically results in greater impacts, as more individuals are exposed to potential flood hazards.

Table 6: *Sensitivity analysis of the disaster index.*

Variables	Sensitivity
Altitude	23.5
Speed	32.8
Area Coverage	12.3
Temperature	10.5
Humidity	4.9
Population Density	16.0

IV. Limitations and Scope of Future Work

The limitations and scope of future work are as follows:

- One limitation of this study is the reliance on historical data for model training, which may introduce biases based on past disaster events. Such biases can limit the model's ability to generalize and accurately predict disaster scenarios that differ significantly from those previously encountered. Additionally, the statistical assumptions inherent in SEM may not always hold true in the complex and dynamic environment of disaster management.
- Another limitation is the potential for sensor inaccuracies in the UAV systems utilized in data collection. Factors such as environmental conditions and technical malfunctions can lead to variability in the input variables, thereby affecting the reliability and precision of the predictions made by the models. This variability necessitates careful calibration and validation of the UAV systems to ensure consistency in the data used for analysis.
- Furthermore, the study focuses primarily on specific input variables, such as altitude, speed, and population density, which may not encompass all critical factors influencing disaster severity. Variables like socioeconomic factors, infrastructure resilience, and local governance mechanisms are also significant in real-world disaster scenarios but were not included in the current modeling approach. Ignoring these additional variables could limit the comprehensiveness of the disaster index and its applicability in diverse contexts.
- Lastly, the proposed deep learning model, while demonstrating a high $r2$ score, may exhibit overfitting if not appropriately regularized. Overfitting can lead to a model that performs well on training data but poorly in real-world applications, where new, unseen data may differ from the training set. Continuous monitoring and updating of the model based on incoming data will be necessary to maintain its accuracy and reliability over time.

V. Conclusion

The present study demonstrates the potential of integrating statistical mode with deep learning techniques, specifically MLP for the prediction of efficient disaster severity. The disaster severity was classified into three levels: low, moderate, and extreme. The structural equation model demonstrates that Altitude, Speed, Area Coverage, Temperature, and Humidity has a significant impact on the disaster index with a p-values less than 0.001. All of the significant variables are taken as the input variables for the MLP model. The MLP model achieves an r2 score of 0.86 for the prediction of disaster severity. The study highlights several limitations, including challenges related to data acquisition and the generalizability of the model to diverse environments. The current model focuses primarily on data, and incorporating other data sources such as ground-based sensors or weather information could improve its robustness. Additionally, the sensitivity analysis shows that UAV speed plays an important predictor of disaster index. Future research should address these limitations by expanding the model's capabilities to handle multimodal data and adapt to changing conditions in real-time. In conclusion, this study provides a strong foundation for the use of UAV based deep learning systems in disaster management, particularly for emergency response and resource allocation. The high regression accuracy and real-time decision-making potential of this model make it a valuable tool for disaster identification.

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