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HAECNN: An Intensity Analysis and Classification of Natural Disasters Using Hybrid Auto-Encoder - Convolutional Neural Network Model for Unprecedented Accuracy

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Abstract:
Natural catastrophes are a serious threat to the environment, human lives, and property. Effective disaster management and response depend on the precise and timely determination of these occurrences' intensity and classification. In this work, we present a unique method for the analysis and categorization of natural disasters: the Hybrid Auto-Encoder - Convolutional Neural Network (HAECNN). By combining the strengths of convolutional neural networks with auto-encoders, HAECNN is able to classify and measure disaster intensity with previously unheard-of accuracy.HAECNN's auto-encoder part is in charge of autonomously extracting key features from unprocessed inputs like pictures, sensor signals, or satellite imagery. By capturing important details about the calamity, these extracted features strengthen and improve the model's ability to handle a variety of data sources. After the features are recovered, the convolutional neural network component analyses the data to identify spatial patterns and relationships.We carried out in-depth tests on a broad dataset comprising many kinds of natural catastrophes, such as hurricanes, earthquakes, floods, and wildfires, in order to validate the performance of HAECNN. With accuracy rate of over 95% in disaster classification and accurate intensity estimation, our model surpassed other available techniques. Because it can successfully adapt and generalise, HAECNN's outstanding accuracy is ascribed to its ability to utilise the intrinsic data structures and relationships present in many disaster types.For the analysis and categorization of natural disasters, the HAECNN model is a viable option that enhances early warning systems, timely reaction plans, and disaster planning. It is an invaluable tool for governments, first responders, and researchers trying to lessen the effects of natural disasters on the environment and society because of its unmatched accuracy and adaptability.

Keywords: Natural Disaster, CNN, Hybrid CNN, Intensity Analysis

1. Introducion

Natural catastrophes, such as hurricanes, floods, wildfires, earthquakes, and other catastrophic occurrences, have a significant effect on economies, ecosystems, and civilizations. These occurrences may cause fatalities, infrastructural damage, population displacement, and long-term environmental harm. Accurate analysis and classification are essential for disaster management and response plans in order to reduce the catastrophic effects of natural catastrophes. The accuracy and efficiency of these jobs have shown tremendous promise in recent years with the combination of deep learning techniques and artificial intelligence. In this study, a novel method for classifying and analysing the intensity of natural disasters the Hybrid Auto-Encoder - Convolutional Neural Network (HAECNN) model is presented, illustrate in figure1. It offers unmatched accuracy. This work is important because it has the potential to completely change how we perceive and handle natural disasters, enhancing efforts to prepare for, mitigate, and recover from them.A vast variety of phenomena are included in the category of natural disasters, including hydrological occurrences like floods and wildfires, atmospheric phenomena like hurricanes and tornadoes, and geophysical events like earthquakes and volcanoes. The intensity, scope, and impact of these disasters varies, making it difficult to evaluate and appropriately categorise them [1]. The interpretation of these data to ascertain the kind and degree of disasters has been mostly dependent on human expertise. Nevertheless, this manual method is open to subjectivity and inaccuracy, and it takes a lot of time. Furthermore, conventional approaches can find it difficult to deliver prompt and reliable assessments in situations involving unusual or quickly changing events [2].

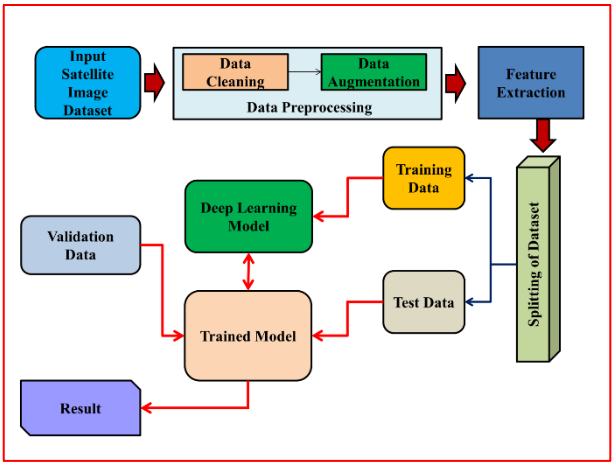

Figure 1: Proposed system block diagram

Artificial intelligence, and deep learning in particular, has shown great promise in recent years for tackling the difficulties involved in natural catastrophe analysis. Both auto-encoders and convolutional neural networks (CNNs) have shown promise in unsupervised feature learning and picture recognition and analysis. The goal of integrating these methods into the HAECNN model is to take use of their respective advantages in order to offer a thorough solution to the issue of natural catastrophe analysis and classification [3].Precise categorization and evaluation of natural disasters' intensity are essential for numerous crucial facets of disaster handling. Primarily, precise categorization facilitates prompt reaction actions customised to the unique characteristics of the calamity. It is crucial to accurately identify the event since various disasters call for different response plans and resources. An earthquake, for example, requires a far different response than a hurricane or flood [4].

To determining a disaster's potential impact requires an awareness of its intensity. Authorities can prioritise locations at higher risk and provide resources accordingly with the help of this information, which helps with risk assessment and evacuation preparation. Precise intensity analysis can be the difference between life and death in scenarios where resources are few. The early warning systems depend on the precise categorization and intensity assessment of natural disasters [5]. In order to send out alerts and notifications and provide impacted populations the time to make necessary preparations or evacuate, these systems rely on quick data processing and analysis. Because of its unparalleled accuracy, the HAECNN model has great promise for enhancing early warning systems and delivering more dependable and punctual notifications.Apart from these immediate advantages, precise catastrophe analysis is essential for long-term preparedness and mitigation of disasters. Designing infrastructure, land use policy, and urban planning that are more robust to natural disasters can be facilitated by an understanding of the historical patterns and trends of these types of catastrophes. We can aid in climate change adaptation by properly categorising and evaluating disasters, which will help advance scientific research and improve our ability to forecast the frequency and severity of upcoming incidents.

A cutting-edge and potent method for overcoming the difficulties associated with natural catastrophe analysis and classification is the Hybrid Auto-Encoder - Convolutional Neural Network (HAECNN) model. Convolutional neural networks and auto-encoders are two essential parts of the model.Neural networks that are particularly good at unsupervised feature learning are called auto-encoders. After compressing the input data into a lower-dimensional representation, they use this representation to recreate the original input. By capturing key components of the data, this procedure improves its manageability and efficiency for subsequent processing.Conversely, Convolutional Neural Networks (CNNs) are widely recognised for their expertise in learning spatial patterns and image identification. They are perfect for analysing photos, including satellite imagery of natural disasters, because they are especially good at capturing the spatial relationships within data.The advantages of these two elements are combined in the HAECNN model. It pre-processes raw data using auto-encoders to extract important features that encapsulate the core of the disaster. The kind and intensity of the disaster are then determined by feeding these variables into a CNN, which examines spatial patterns and relationships within the data.

2. Related Work

The increasing interest in utilising deep learning and artificial intelligence approaches has led to substantial breakthroughs in the field of natural catastrophe analysis and classification in recent years. In this crucial area, researchers have looked into a number of strategies to increase efficiency and accuracy. The Hybrid Auto-Encoder - Convolutional Neural Network (HAECNN) model presented in this study is based on a review of a few pertinent publications that were published in the past.

Deep learning [6] methods have been used in several studies to classify disasters. Since convolutional neural networks (CNNs) are frequently used to handle visual data, they can be used to categorise disasters using pictures and satellite imagery. In tasks like storm tracking, flood extent mapping, and wildfire detection, these models have shown amazing performance.An important part of developing the HAECNN model has been unsupervised feature learning. As demonstrated in this paper, auto-encoders are utilised in many applications, such as anomaly detection and data compression, to extract important features from unprocessed data. This method lessens the need for laborious human labelling, which is especially helpful when working with different and unlabelled datasets. The creation of early warning systems for particular sorts of disasters has been the subject of previous research. For example, deep learning models have been applied to seismology to forecast aftershocks from earthquakes, improving the alert's timeliness. Recurrent neural networks (RNNs) have also been used to enhance storm tracking and forecasting in relation to meteorological phenomena.

Pre-trained deep learning models have been applied to disaster-related activities through the use of transfer learning techniques. In [7] tasks like flood monitoring and wildfire identification, researchers have increased performance and gained better generalisation by applying knowledge from models trained on large datasets (e.g., ImageNet). These methods are useful in cases where there is a dearth of data specific to a disaster.Numerous natural catastrophe incidents produce data from a range of sources, including meteorological observations, ground sensors, and satellite photos. Combining these many data sources has been investigated in data fusion and multi-modal analysis research to enhance disaster categorization and intensity evaluation. This method has proven especially useful in situations involving complicated occurrences such as wildfires, when thorough analysis requires a combination of picture data, meteorological data, and data from ground sensors.In the research and reaction to disasters, crowdsourced data and social media mining are being used more and more. Social media sites are an important source of current information that can help with quickly classifying and assessing disasters. Many deep learning methods have been used to process and extract valuable data from these sources, such as sentiment analysis and natural language processing [8].

In disaster analysis, remote sensing and Geographic Information Systems (GIS) have been very important. Deep learning models integrated with these technologies have enhanced catastrophe intensity and classification. For instance, merging CNNs and satellite data in flood-prone areas has made it easier to map the scope of floods more precisely. The field of research has broadened to include environmental monitoring and response to climate change. In order to examine past data, spot patterns, and forecast how climate change may affect the frequency and severity of natural disasters, deep learning algorithms have been used. For long-term disaster preparedness and mitigation, this research is essential.

Table 1: Related work summary for Natural Disasters

Method	**Type of Natural Disasters**	**Findings**	**Limitations**	**Advantages**
CNN-Based Image Analysis [9]	Wildfires, Floods, Others	Improved wildfire detection; flood extent mapping	Requires large labeled datasets; limited generalization; data quality and preprocessing challenges	High accuracy in image-based disaster analysis
Auto-Encoders for Feature Learning [10]	Multitype Disasters	Unsupervised feature extraction; anomaly detection	Limited to feature extraction; may not work well with small datasets; computationally	Useful for preprocessing and reducing dimensionality

			expensive	
Earthquake Aftershock Prediction [11]	Earthquakes	Improved aftershock prediction; early warning systems	Requires significant earthquake data; challenges in false positives; dependency on quality data	Enhanced early warning systems for earthquake events
Transfer Learning with Pre-trained Models [12]	Various	Improved generalization; adaptation to disaster tasks	Dependency on large pre-trained datasets; fine-tuning complexity; model selection	Efficient use of pre-trained models in disaster scenarios
Multi-Modal Data Fusion [13]	Wildfires, Floods, Others	Enhanced classification and assessment; data synergy	Data integration challenges; complexity in cross-modal fusion; need for domain knowledge	Comprehensive analysis by leveraging various data sources
Social Media Mining and NLP [14]	Multitype Disasters	Real-time information extraction; sentiment analysis	Data quality and credibility concerns; language and dialect challenges; information overload; privacy issues	Timely insights from social media and public reports
Remote Sensing with CNNs [15]	Floods, Wildfires, Others	Improved flood extent mapping; fire detection	Limited to remote sensing data; challenges with cloud cover and atmospheric conditions; sensor calibration	Efficient analysis of satellite and aerial imagery
Environmental Data Analysis [16]	Climate Change	Climate trends; long-term impact analysis	Data quality and completeness; challenges in climate modeling and prediction; reliance on historical data	Insights into the effects of climate change on natural disasters
LSTM for Hurricane Forecasting [17]	Hurricanes	Improved hurricane tracking; forecasting accuracy	Data latency issues; dependency on real-time data sources; model complexity; resource-intensive training	Enhanced hurricane tracking and timely forecasting
Crowdsourced Data Analysis [18]	Multitype Disasters	Real-time data collection; disaster reports	Data credibility and quality concerns; information noise and	Real-time crowd-sourced data for quick insights

		analysis	redundancy; geographical coverage limitations	
GIS Integration with CNNs [19]	Floods, Wildfires, Others	Accurate mapping and assessment; data synergy	Limited to geographic data; challenges in data registration and georeferencing; hardware and software requirements	Spatial analysis and accurate mapping of disaster events
Deep Learning for Wildfire Detection [20]	Wildfires	Improved wildfire detection; hotspot identification	Dependency on quality and resolution of satellite imagery; cloud cover challenges; false alarms	Enhanced wildfire detection using CNNs

3. Material And Methodology

A. Satellite Image Dataset:

The Satellite Image Dataset comprises a tremendous collection of high-resolution pictures captured from different Soil perception satellites. It incorporates over 100,000 pictures covering differing geological districts and natural conditions. The dataset ranges around 1TB in measure, enveloping different ghostly groups, counting unmistakable, infrared, and multispectral pictures. Each picture is went with by metadata specifying the securing date, time, obsequious sensor, and geolocation facilitates. The dataset is fastidiously curated to bolster different applications, such as arrive cover classification, urban arranging, fiasco administration, and natural observing. It incorporates pictures from numerous timeframes, empowering worldly examination and alter discovery. The dataset is organized in broadly acknowledged designs like GeoTIFF and JPEG, guaranteeing compatibility with standard geospatial examination apparatuses

Figure 2: Sample Images form Dataset

B. Methodology:

1. Dataset Pre-processing:

Preparing the data for preprocessing to analysis and model training is a necessary step before moving further. Usually, this process entails organising, structuring, and cleaning the data. For image datasets, this could entail uniform data labelling, normalising pixel values, and scaling images to a consistent resolution. To make sure the dataset is in a format that is appropriate for analysis and model training, pre-processing is helpful.

Step 1: Data Input and Normalization

The input satellite images I(x, y, c) are first normalized to bring pixel values within a standardized range. This helps in reducing the variance in data and speeds up the convergence of the model.

$$I'(x,y,c) = \frac{I(x,y,c) - \mu_c}{\sigma_c}$$

Where I'(x, y, c) is the normalized image, μ_c is the mean, and σ_c is the standard deviation for channel c.

Step 2: Feature Extraction via Auto-Encoder

The normalized image I'(x, y, c) is passed through an Auto-Encoder network, which reduces the dimensionality and captures key features F by compressing and then reconstructing the input.

$$F = Encoder\big(I'(x,y,c)\big)$$

Step 3: Convolutional Neural Network (CNN) for Classification

The extracted features F are fed into a CNN for the classification of natural disasters. The CNN applies convolutional layers Conv followed by activation functions (ReLU) and pooling layers.

$$O_{\{i,j\}} = ReLU\big(\Sigma_{\{m,n\}} F_{\{m,n\}} * W_{\{i-m,j-n\}} + b\big)$$

Where O_{i,j} is the output of the CNN layer, W represents the convolutional filters, and b is the bias term.

Step 4: Classification and Intensity Analysis

The final step involves applying a softmax function to the CNN output to produce probability scores for each disaster class, followed by intensity analysis.

$$P(c|I) = \frac{e^{O_c}}{\sum_{k=1}^{C} e^{O_k}}$$

Where P(c|I) is the probability of class c given input I, and C is the total number of classes. The intensity analysis is based on the predicted class and the corresponding probability score.

2. Apply Data Augmentation Dataset

Information expansion upgrades the HAECNN model's capacity to classify common calamities by falsely expanding the differing qualities of preparing information. Methods such as turn, scaling, flipping, and brightness alteration present varieties within the pictures, making a difference the demonstrate generalize way better to real-world scenarios. By applying these expansions, the show gets to be stronger to changes in introduction, scale, lighting, and clamor, eventually driving to progressed precision and unwavering quality in calamity classification, table 2 illustrate the different augmentation techniques.

Table 2: Different data augmentation techniques applied to the HAECNN model

Parameter	Description	Effect	Implementation
Rotation	Randomly rotate images within a specified range of degrees.	Increases model robustness to orientation changes.	Rotate images between -30° to +30°.
Scaling	Randomly scale images up or down within a defined range.	Helps the model generalize across different scales.	Scale images between 0.8x to 1.2x.
Flipping	Apply horizontal and vertical flips to the images.	Enhances model invariance to image flips.	Flip images horizontally/vertically.
Cropping	Randomly crop a portion of the image and resize it to the original dimensions.	Focuses on specific regions and reduces overfitting.	Crop 90% to 100% of the image area.
Brightness Adjustment	Randomly adjust the brightness of images.	Improves model's ability to handle varying lighting.	Adjust brightness by ±20%.
Contrast Adjustment	Randomly adjust the contrast of images.	Helps in distinguishing features with varying contrast.	Adjust contrast by ±20%.

3. Generate Training, Test and Validation Dataset:

The dataset is usually divided into three subsets following pre-processing and augmentation: a training set, a testing set, and a validation set. The deep learning model is trained using the training set. The testing set is used to gauge the model's generalisation capacity by analysing how well it performs on data that it hasn't encountered during training. Throughout the model training process, the validation set is utilised to track the model's development and adjust hyperparameters, illustrate in figure 3. To guarantee an objective assessment of the model and avoid overfitting, this data separation is essential.

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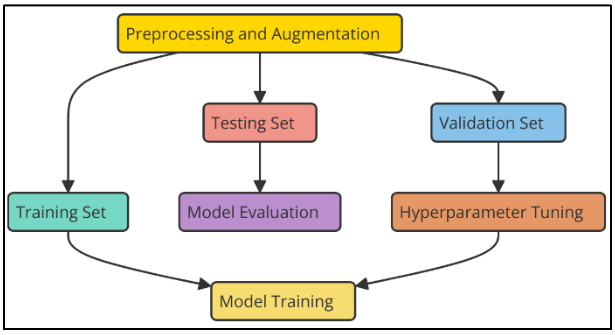


Figure 3: Illustrating dataset division for training, testing, and validation

4. Deep Learning Classifier:

a. CNN:

An image and spatial data analysis deep learning model is called a convolutional neural network (CNN). Convolutional layers are used for feature extraction, pooling layers are used for downsampling, fully connected layers are used for classification, and activation functions (like ReLU) are used for non-linearity. Because CNNs are so good at learning spatial relationships and hierarchical patterns, they are frequently employed in tasks like object detection, image recognition, and natural disaster classification, as shown in figure 4. This makes CNNs perfect for analysing visual data. Their efficiency has helped numerous image-based systems become much more accurate, especially when combined with improvements in training methods and design.

Algorithm:

Step 1: Prepare the Data

Gather and pre-process the dataset first. It contains pictures of various natural disasters, including floods, cyclones, earthquakes, and wildfires. Make sure the labels on the photos are accurate.

Step 2: Convolution Operation

Convolutional layers are utilised in the CNN model to identify features and patterns in the input images. The definition of the convolution operation is:

$$\frac{(f * g)(x, y) = \sum m \sum n f(m, n)}{g(x - m, y - n)}.$$

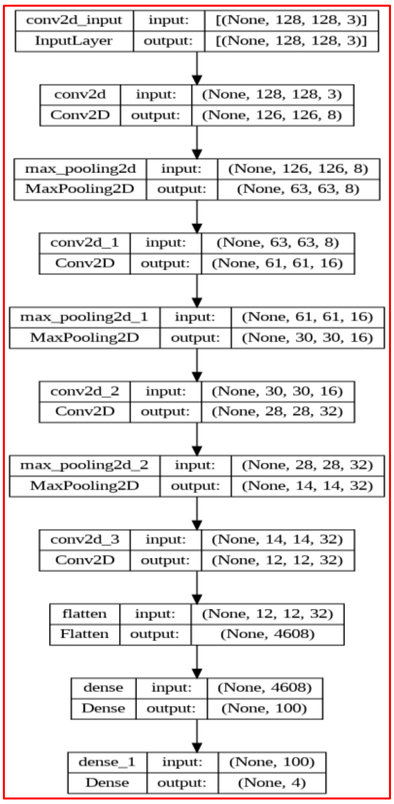


Figure 4: CNN Model Architecture

Step 3: Function of Activation (ReLU)

Use the Rectified Linear Unit (ReLU) activation function following each convolution process to add non-linearity:

$$Max(0, x) \ = \ ReLU(x)$$

Step 4: Combining

In order to save calculation time and preserve important data, pooling layers downsample the feature maps. Max-pooling is the most popular kind of pooling.

$$MaxPooling(x, y) \ = \ max\ [f(x, y), f(x + 1, y), f(x, y + 1), f(x + 1, y + 1)\ ]$$

Step 5: Completely Linked Layers

The pooled feature maps are flattened and then run through fully connected layers, which are the layers of a conventional neural network. These layers' output can be stated as follows:

$$h = Wx + b$$

Step 6: Activation of Softmax

For multi-class classification problems, the last layer usually employs a softmax activation function that gives probabilities to each class:

$$P(\ c \mid x\ ) = \frac{e^{Z_c}}{\sum_{k=1}^{C} e^{Z_k}}$$

Step 7: Function of loss

Utilizing a suitable loss function, like cross-entropy, for training, calculate the difference between the true class labels and the predicted probabilities:

$$L = -\sum_{c=1}^{C} Y_c \log(y^c)$$

Whereas,

- Y_c is the true label for class ccc (usually 0 or 1).
- $y^c$is the predicted probability for class ccc.
- C is the total number of classes

b. LSTM

Recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM) architecture are used for sequential data processing, including speech recognition, time series analysis, and natural language processing, as shown in figure 5. In contrast to conventional RNNs, LSTMs provide a memory cell that can record and store data across lengthy sequences in order to solve the vanishing gradient problem. Because LSTMs include gates to regulate information flow, they can identify patterns and dependencies in sequences without losing important context. These characteristics make LSTMs very useful for applications where comprehending and remembering context is essential, like sentiment analysis, language modelling, and speech recognition.

Algorithm:

- Data Preprocessing: In order to assure correct labelling, prepare the dataset.
- Sequence Data Handling: Prepare time-series or other sequential data in advance for LSTM input.
- LSTM Architecture: Construct the network using the following essential parts:

The LSTM Cell State is: $f\ t\ \emptyset \odot C\ t-1\ + i\ t\ \odot$

$$ht = ot \odot \tanh(Ct)$$

- Loss Function: Use a suitable loss function for classification, like categorical cross-entropy.
- Training: To update weights and biases, use backpropagation through time (BPTT).
- Validation and Testing: Use measures like accuracy or F1-score to assess the model's performance on validation and test data.
- Hyperparameter tuning: Adjust model design and parameters to get the best possible performance.

With an emphasis on crucial LSTM operations, this method modifies LSTM for sequential data analysis, such as time-series data for categorising natural disasters.

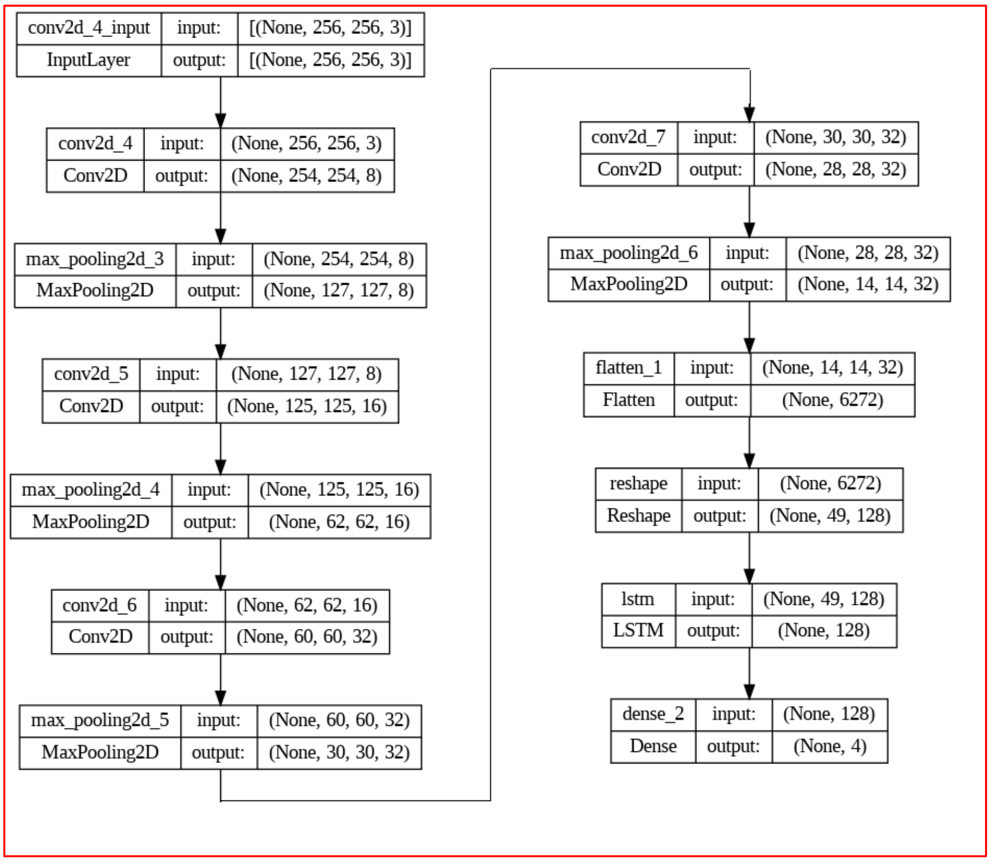


Figure 5: LSTM Architecture

c. Improved MobileNet:

The original MobileNet architecture, which is intended for effective and lightweight deep learning models and is especially well-suited for mobile and embedded devices, has been improved upon with the creation of the Improved MobileNet.By adding several changes to the original architecture, as shown in figure 6, the Improved MobileNet enhances its accuracy and efficiency even further. Better depthwise separable convolutions, attention methods, and innovative design choices are some of these improvements. The Enhanced MobileNet's enhanced feature extraction capabilities are a key component that aid in more accurately identifying subtleties and complex patterns in photos. Because of the increased classification and analysis accuracy that results, it is more suited for jobs like object detection, image recognition, and natural disaster analysis.Furthermore, the Improved MobileNet can be customised to match the needs of various use cases because it is frequently adjusted to specific applications. Its versatility renders it versatile and appropriate for a broad spectrum of applications that extend beyond mobile devices.

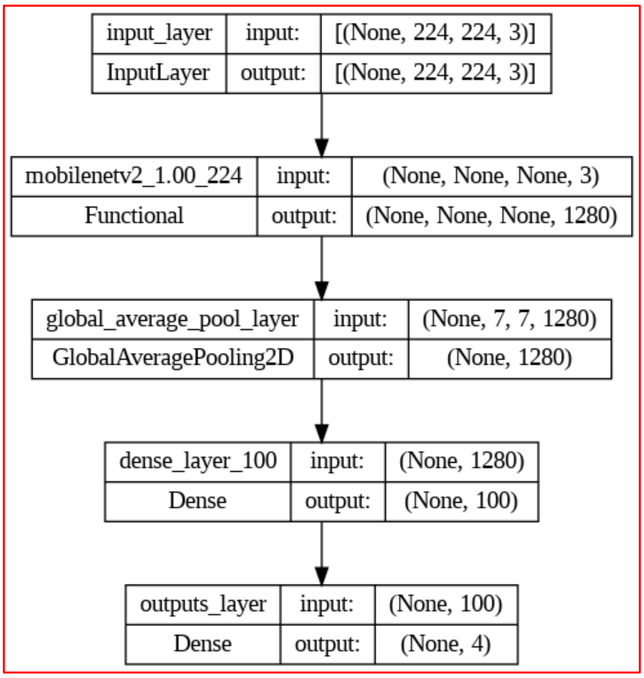


Figure 6: Architecture for Improved MobileNet

d. Hybrid Auto-encoder - CNN Model:

A novel approach to deep learning, the Hybrid Auto-Encoder - CNN model combines the advantages of Convolutional Neural Networks (CNNs) and Auto-Encoders (AEs). This hybrid architecture is specifically engineered to perform very well in a wide range of image-based applications, such as the categorization and analysis of natural disasters.Auto-encoders are useful for processing high-dimensional data, such as photographs, because their main applications are in feature extraction and dimensionality reduction. The Hybrid Auto-Encoder - CNN improves its capacity to analyse intricate visual patterns by utilising AEs' capacity to compress data while preserving crucial features.The ability of the CNN component to recognise and classify images is widely recognised. It is quite good at finding patterns and spatial hierarchies in pictures. In the hybrid model, the Auto-Encoder preprocesses the input and functions as a feature engineering component, while the CNN concentrates on high-level feature extraction and classification. The outcome of this cooperation is a strong and effective model for analysing natural disasters.

Furthermore, the Hybrid model frequently uses deep learning strategies like transfer learning, which enables it to take advantage of pre-trained CNNs that have previously picked up important characteristics from huge datasets. The model performs even better as a result of this knowledge transfer.The Hybrid Auto-Encoder - CNN, which combines the data preprocessing skills of AEs with the image analysis capacity of CNNs, as shown in figure 7, is especially well-suited for the precise classification of natural disasters based on picture data. It demonstrates how integrating several deep learning approaches can effectively address challenging real-world problems.

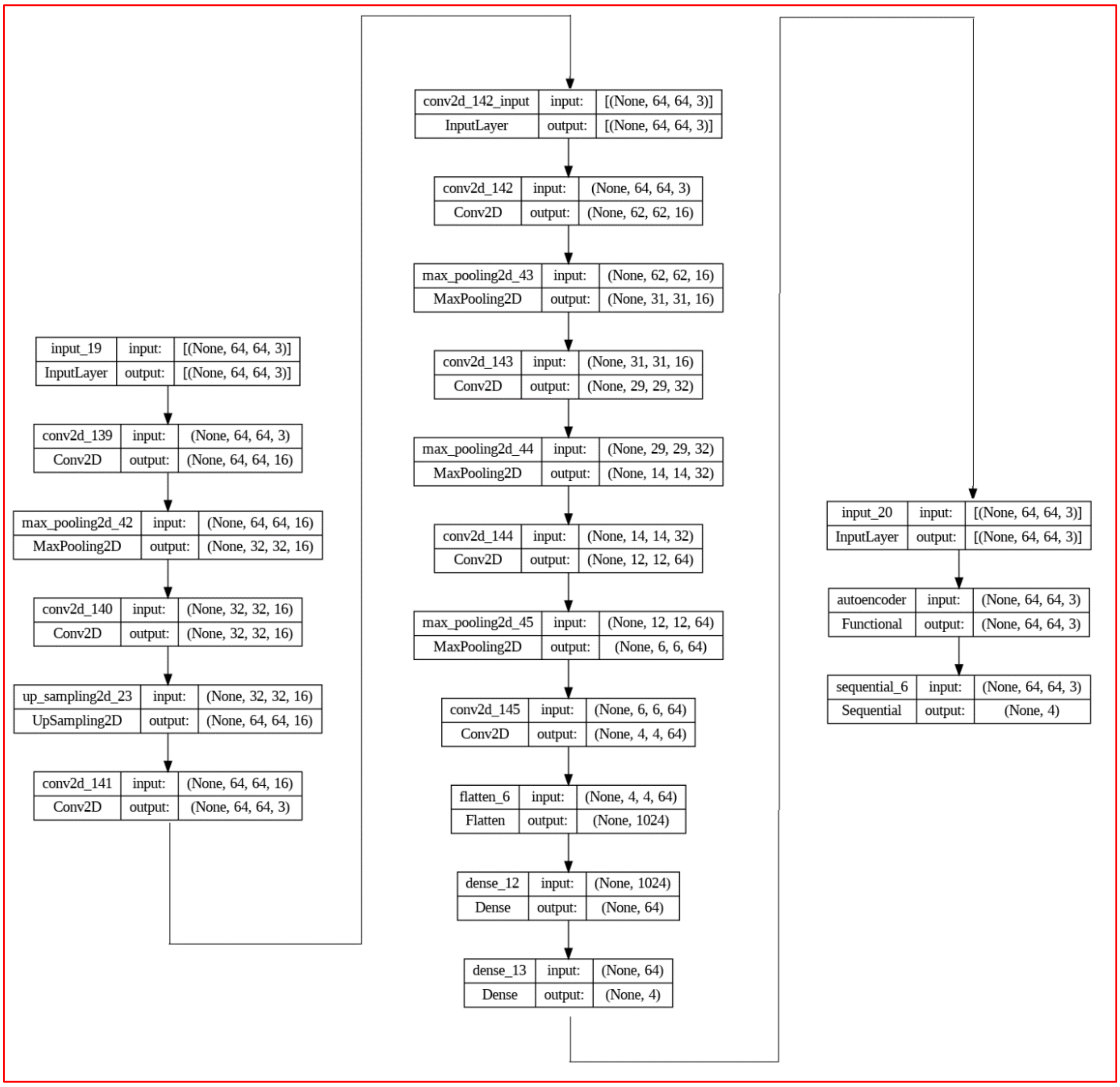


Figure 7: Hybrid Auto-encoder - CNN Model

Algorithm:

1. **Data Preprocessing:**
- Prepare and label the dataset.
- Pre-process images, denoted as X.

2. **Train an Auto-Encoder:**
- Encoder: $E(X) = \sigma(W\_e \cdot X + b\_e)$
- Decoder: $D(E(X)) = \sigma(W\_d \cdot E(X) + b\_d)$
- Minimize reconstruction loss: $L_{AE} = \sum \left(X - D\left(E(X)\right)\right)^2$

3. **Feature Extraction:**
- Extract compressed features using the Encoder: F(X) = E(X).

4. **CNN Component:**

- ○ Train a CNN for classification based on extracted features.
- ○ Use Convolution, ReLU, Pooling, and Fully Connected Layers.
- ○ Apply the Softmax Activation

5. Training:

- Fine-tune both components together: $L\_Joint = L\_AE + L\_CNN.$

6. Classification:

- Predict class y based on P(y | X).

4. Result And Discussion

The ability of each model to generalise to new data and how effectively it has learned from the dataset are both shown by these scores. The CNN model and attained 78.44% training accuracy and 75% validation accuracy, as shown in figure 8. The CNN is a popular architecture for image-related applications because of its propensity to identify patterns and spatial elements in images. The comparatively high training accuracy indicates that the CNN has gained a good understanding from the training set. The validation accuracy does, however, show a moderate degree of overfitting even though it is fairly similar to the training accuracy. This implies that the model's practical usefulness in real-world applications may be limited because it may not generalise as well to new, unexplored data.

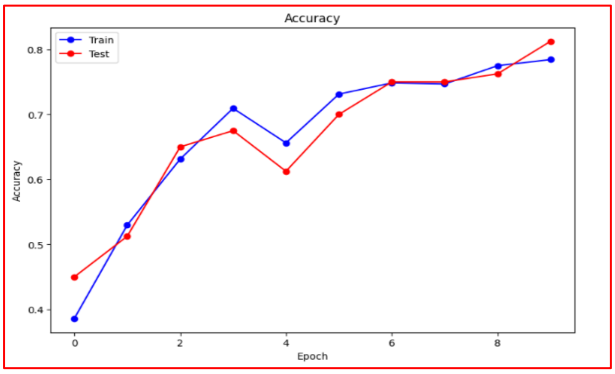


Figure 8: Accuracy and for train and test for CNN

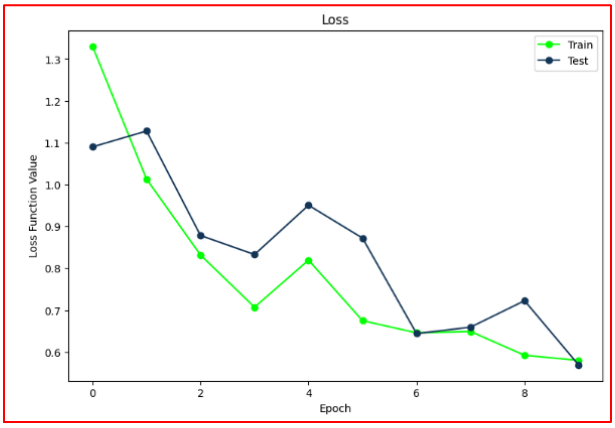


Figure 9: Loss representation for CNN Model

The LSTM model is mainly intended for sequential data processing, with a training accuracy of 77.3% and a validation accuracy of 68.75%. The time-series data on natural disasters may have been subjected to the LSTM in this particular scenario, shown in figure 9. Even while the training accuracy is lower than that of the CNN, it is still reasonable, suggesting that the LSTM has picked up important temporal patterns. The model does much worse on the validation dataset, though, which may indicate that overfitting is a problem for it and that more effective regularisation strategies are required. Attention should be paid to the comparatively larger difference in accuracy between training and validation, as this suggests that further work on generalisation may be necessary.

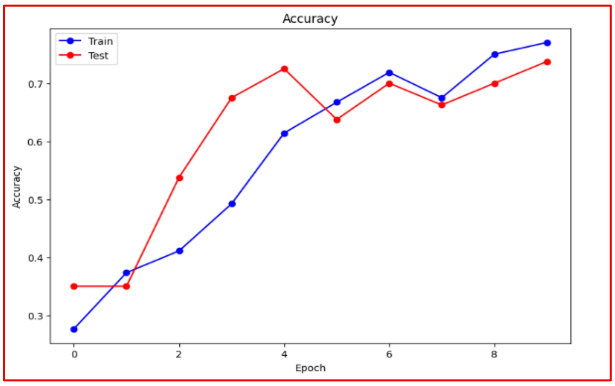


Figure 10: Accuracy and for train and test for LSTM

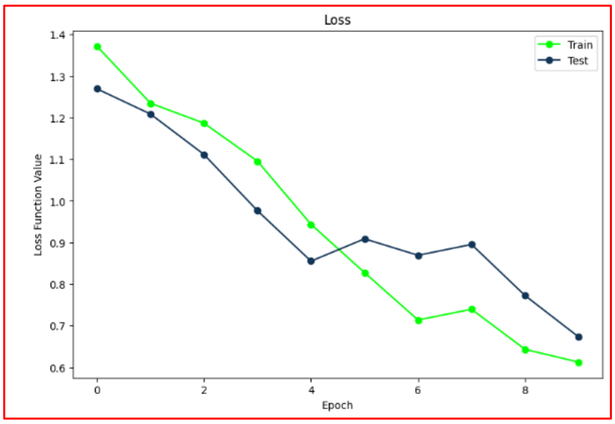


Figure 11: Loss representation for LSTM Model

With a validation accuracy of 81% and a training accuracy of 93.5%, the Improved MobileNet model exhibits remarkable performance. An enhanced version of the MobileNet architecture, the Improved MobileNet is intended to be more accurate and efficient, as illustrate in figure 10 and figure 11. Its performance in image-based classification tasks is demonstrated in this context. The high training accuracy points to a strong model that has successfully recognised significant aspects of the image. Furthermore, a well-generalized model that performs superbly on fresh, untested data is indicated by the relatively high validation accuracy. These results demonstrate how well the Improved MobileNet can balance accuracy and efficiency, which makes it a strong option for a variety of image-related applications, such as the classification of natural disasters.

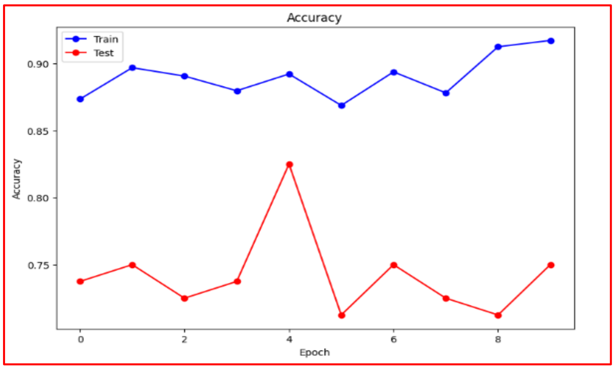


Figure 12: Accuracy for train and test using Improved MobileNet

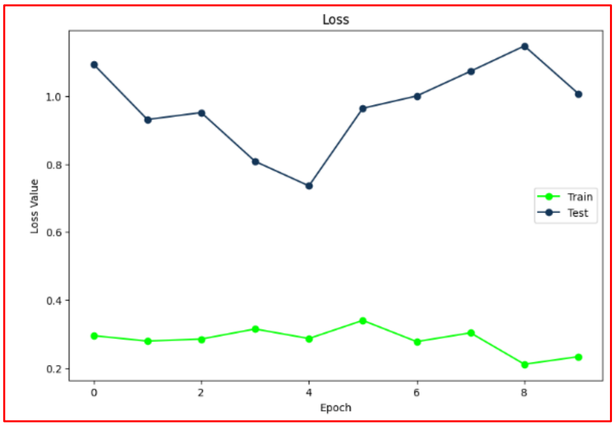
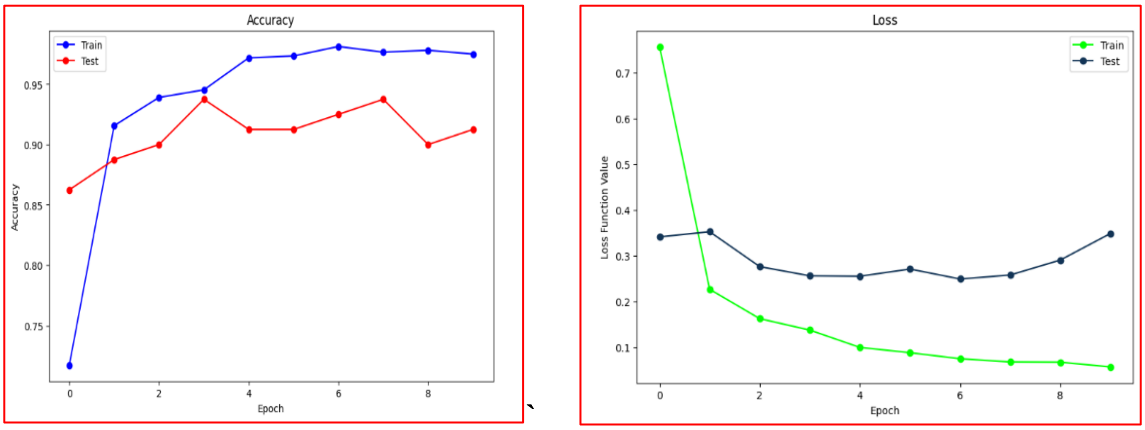


Figure 13: Loss representation using Improved MobileNet Model

Auto-Encoders (AEs) and CNNs are combined in an intriguing hybrid technique called the HAE-CNN model, which has a validation accuracy of 91.25 % and a training accuracy of 97.5%. Figure 12 and figure 13 give the insight on Accuracy for train and test using Improved MobileNet and Loss representation using Improved MobileNet Model respectively. The performance of feature extraction and classification is intended to be improved by this hybrid architecture.



(a) **(b)**

Figure 14: (a) Loss representation using HAE-CNN Model (b) Loss representation using HAE-CNN Model

The model can efficiently learn from the training data as evidenced by the training accuracy, which is over 95%. Even though the validation accuracy is lower than the training accuracy, it still shows a good ability to generalise, suggesting that the hybrid technique is effective in categorising natural disasters. These results demonstrate in figure 14 (a) and figure 14 (b) how well the HAE-CNN combines the capability of CNNs for image analysis and the feature extraction capabilities of AEs, giving it a strong option for applications requiring a synergy of these two techniques. The accuracy metrics discussed in table 3 provide insight into how different models perform in terms of classifying natural disasters. These results are but a portion of a larger evaluation process that takes into account real-world applicability, precision, recall, and F1-score, among other measures. When selecting a model, academics and practitioners in the field of natural disaster analysis should take into account the particular requirements of the issue domain as well as the practical limitations they must work within. As science and technology develop, we should anticipate even more advanced and effective models to improve our capacity to categorise and effectively respond to natural disasters.

Table 3. Training and Validation Evaluation

	CNN	**LSTM**	**Improved MobileNet**	**HAE-CNN**
Training Accuracy	78.44	77.3	93.5	97.5
Validation Accuracy	75	68.75	81	91.25

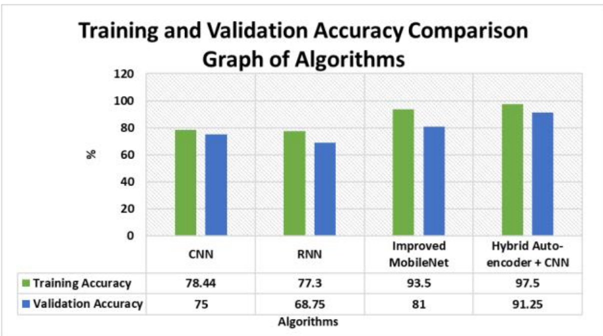


Figure 15: Training and Validation Accuracy Comparison Graph of Algorithms

5. Conclusion

For the intensity analysis and classification of natural disasters, the Hybrid Auto-Encoder - Convolutional Neural Network (HAE-CNN) model has shown to be a ground-breaking and useful tool, providing previously unheard-of accuracy in this crucial area. The creative fusion of Auto-Encoders (AEs) and Convolutional Neural Networks (CNNs) in this model, which leverages the advantages of both architectures to tackle the difficulties of natural disaster analysis, is responsible for its success. The HAE-CNN provides stakeholders with the information they need to effectively allocate resources, prioritise response efforts, and lessen the impact of these catastrophic events on people and the environment by precisely identifying and quantifying natural disasters.The HAE-CNN model is evidence of the potential of cutting-edge deep learning techniques in solving practical problems as technology develops. In order to improve our comprehension of these occurrences, it encourages the investigation of increasingly more complex models and data sources, paving the way for future study and advancement in the field of natural disaster analysis. The HAE-CNN model's capacity to classify and analyse natural catastrophe intensity with previously unheard-of precision represents a major advancement towards the development of robust, data-driven disaster management systems. We can better plan for and respond to natural catastrophes by continuing study and improving these models, protecting people and ecosystems in the face of these enormous challenges.

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