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Weather Dataset Classification Using Deep Learning Algorithms

Navita

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Abstract: The goal of the research project "Weather Dataset Classification Using Deep Learning Algorithms" is to assess how well the Multi-Agent System Decision Support System (MAS-DSS) architecture performs and how well it enhances weather forecasting decision-making. Three main goals are being pursued: first, evaluating the influence of the MAS-DSS framework on organizational outcomes, user satisfaction, and decision-making efficiency in weather-related applications; second, assessing the framework's efficacy in enhancing the precision and dependability of weather dataset classification through the use of cutting-edge deep learning algorithms; and third, investigating the MAS-DSS framework's scalability and adaptability in various domains and decision contexts. Utilizing a blend of convolutional neural networks (CNNs) and further deep learning methodologies, the research applies the MAS-DSS framework to an extensive assortment of meteorological datasets. Metrics for user happiness, recall, accuracy, and precision in categorization are used to gauge the framework's effectiveness. The findings show notable gains in user satisfaction and decision-making effectiveness, with improved organizational outcomes as a result of more precise and trustworthy weather forecasts. The research also investigates the framework's scalability, showing that it may be used to a variety of areas outside of weather forecasting. This study demonstrates how deep learning algorithms may be integrated with the MAS-DSS architecture to transform decision support systems across a range of application domains.

Keywords: *CNN, MAS-DSS, deep learning*

1. Introduction

A number of different industries, such as agriculture, aviation, crisis management, and activities that people engage in on a daily basis, have traditionally relied heavily on weather forecasting. In order to plan for and mitigate the negative consequences that are created by extreme weather conditions, accurate weather predictions are helpful. In the past, the process of forecasting the weather depended mainly on numerical weather prediction (NWP) models. These models mimic the behavior of the atmosphere by employing physical equations. These models, while useful to a certain extent, frequently struggle with the complex patterns and non-linear interactions that are inherent in meteorological data, which contributes to limitations in the accuracy of their predictions.

With the development of machine learning, and more specifically deep learning, several areas, including meteorology, have been transformed in recent years. Deep learning models, such as convolutional neural networks (CNNs), have demonstrated exceptional performance in a variety of situations involving image and pattern recognition. These models have the ability to learn from enormous volumes of data and recognize nuanced patterns that standard approaches could overlook. The application of deep learning in the field of weather forecasting has the potential to enhance accuracy by capturing the intricate and non-linear correlations that are inherent in meteorological data.

Specifically, the aim of this article is to investigate the utilization of deep learning algorithms for the categorization of meteorological datasets, with a particular emphasis on assessing the Multi-Agent System Decision Support System (MAS-DSS) architecture. Through the incorporation of cutting-edge machine learning strategies and decision support systems, the MAS-DSS architecture makes it possible to improve decision-making procedures. The purpose of this article is to evaluate the overall efficacy of the framework, as well as its influence on organizational outcomes, user happiness, scalability, and flexibility across a variety of decision situations and domains. The goal of the MAS-DSS framework is to improve the accuracy and reliability of weather forecasts by utilizing deep learning algorithms. This will ultimately lead to an increase in the efficiency of decision-making and the level of pleasure experienced by users. This research will apply the MAS-DSS framework to a variety of meteorological datasets in order to evaluate its performance in terms

Research scholar in computer science and application

PDM University, Bahadurgarh, jhajjar, India

of classification accuracy, precision, recall, and other metrics that are pertinent to the study. In addition to this, the project will investigate the scalability and adaptability of the framework to a variety of areas that go beyond weather forecasting.

1.1 Objectives of the Paper

The primary objectives of this paper are as follows:

- Evaluate the effectiveness and performance of the MAS-DSS framework in enhancing decision-making processes: The primary purpose is to conduct a comprehensive evaluation of the degree to which the MAS-DSS framework is able to effectively integrate with deep learning algorithms in order to enhance decision-making procedures. In order to strengthen the quality of judgments that are made based on these forecasts, it is necessary to conduct an analysis of the framework's capacity to properly analyze and categorize meteorological data.
- Assess the impact of the MAS-DSS framework on organizational outcomes, user satisfaction, and decision-making efficiency: The second purpose is to determine the extent to which the MAS-DSS framework has an effect on the various results realized by the company. This involves determining how the enhanced weather predictions affect the efficiency of operations, the management of risks, and the planning of strategic actions. Another important indicator is user satisfaction, which is important since the usability and dependability of the framework have a direct impact on how users view it and how much they embrace it.
- Explore the scalability and adaptability of the MAS-DSS framework to different domains and decision contexts: Investigating the adaptability and scalability of the MAS-DSS system is the third goal of this project. In order to establish the framework's adaptability to a variety of decision-making situations, this requires evaluating its applicability in a variety of areas that are not related to meteorology, such as agriculture, logistics, and environmental management. The purpose of this investigation is to determine whether or not the framework can be easily generalized and successfully applied to a variety of situations.

1.2 Deep Learning in Weather Forecasting

The subject of weather forecasting has made great progress thanks to the use of deep learning. In spite of the fact that they are fundamental, traditional NWP models sometimes call for a substantial amount of processing resources and struggle to deal with the granularity of data that is necessary for accurate local forecasts. Deep learning models, and CNNs in particular, are especially effective at processing big datasets and identifying significant patterns, which makes them an excellent choice for task involving weather categorization. These models are able to learn to detect patterns associated with various weather situations by training on past meteorological data, which ultimately results in an improvement in the accuracy of forecasts they provide.

CNNs, for instance, have been effectively utilized in a variety of meteorological research for the purpose of categorizing weather occurrences, forecasting precipitation, and even identifying catastrophic weather events such as hurricanes and tornadoes. Because of their resilience in feature extraction and its capacity to handle spatial data, CNNs are particularly well-suited for the tasks that are associated with these jobs. The purpose of this research is to improve the accuracy and reliability of weather forecasts by incorporating CNNs inside the MAS-DSS framework. This paper builds on the foundation that was built before.

1.3 The MAS-DSS Framework

A comprehensive foundation for improved decision-making is created by the MAS-DSS framework, which integrates the strengths of decision support systems and multi-agent systems based on their respective strengths. In multi-agent systems, there are several intelligent agents that are able to communicate with one another and work together to find solutions to difficult issues. From the perspective of weather forecasting, these agents are able to manage many parts of the data processing and prediction duties, therefore boosting both the efficiency and accuracy of the forecasting process.

Decision support systems, often known as DSS, are software-based systems that are interactive and integrated with data, complex analytical models, and user-friendly software. They are designed to aid in the process of decision-making. The MAS-DSS framework makes use of the predictive capability of these models by combining deep learning algorithms. This allows the framework to deliver weather forecasts that are correct and come at the appropriate moment. Through the provision of more trustworthy data and insights, this integration intends to enhance the decision-making process as a whole.

Using a mix of convolutional neural networks (CNNs) and other deep learning approaches, the research project will build the MAS-DSS framework in order to accomplish the goals that have been specified. In order to guarantee a thorough review, the framework will be tested on a variety of meteorological datasets. Various meteorological factors, including temperature, humidity, wind speed, and air pressure, will be included in the datasets. These values will be obtained from a variety of independent sources. Metrics such as classification accuracy, precision, recall, and user satisfaction will be utilized in the study's assessment procedure, which will be rigorous. Surveys and case studies will be used to collect feedback from users in order to quantify the impact that the organization's outcomes have had. The framework will also be put through its paces by being used to a variety of decision situations and domains in order to evaluate its flexibility and scalability.

By proving the efficacy of integrating deep learning with the MAS-DSS architecture, it is anticipated that this research will make a substantial contribution to the area of meteorology as well as decision support systems. The findings will shed light on the myriad advantages that may be gained from employing sophisticated machine learning strategies for the purpose of weather categorization and forecasting. Additionally, the research will provide insight on the potential for scalability and applicability of the framework to a variety of areas, therefore opening the path for applications that are more widespread.

This study intends to provide a holistic solution for improving weather predictions and decision-making processes by tackling the issues of accuracy, efficiency, and user satisfaction. Specifically, their focus is on addressing these challenges. All those practitioners and academics who are interested in enhancing the capabilities of their decision support systems via the application of deep learning techniques will find the insights acquired from this research to be quite beneficial. It can be concluded that the incorporation of deep learning algorithms into the MAS-DSS framework is a significant achievement in the field of decision support systems and weather forecasting. Within the scope of this article, we intend to assess the efficacy of the framework, as well as its impact on organizational results and its scalability across a variety of disciplines. The MAS-DSS framework is prepared to improve decision-making processes, increase accuracy, and give more trustworthy weather forecasts. This will be accomplished by utilizing the capabilities of CNNs and other deep learning models. By highlighting the potential of deep learning to revolutionize a variety of application domains, this research will contribute to the continuous development of advanced decision support systems and bring attention to the promise of deep learning.

2. Literature Review

Mittal Shweta et al. [1] (2023) proposed a system that makes use of transfer learning for the purpose of categorizing weather photos. This framework makes use of features derived from deep CNN models that have already been trained in order to get results in a substantially shorter amount of time. They brought attention to the influence that the magnitude of the training data has on the efficiency of the model, pointing out that a greater quantity of high-quality data often results in an increase in accuracy. In order to accommodate huge datasets, the framework that has been presented has been developed on the Spark platform. This ensures that the framework is both scalable and resilient. The dependability of the framework has been demonstrated by extensive trials carried out on a dataset consisting of weather images. The results of the study reveal that the optimal performance is achieved by combining the InceptionV3 model with a Logistic Regression classifier. This combination achieves a maximum accuracy of 97.77%. These findings demonstrate that merging transfer learning with scalable big data platforms is an effective method for performing weather categorization jobs.

Dalal, S et al. [2] (2023) addressed constructing an effective weather classifier that just requires a single image as input in order to solve issues related to quality of life. A modified deep learning strategy was suggested by them. This method was based on the YOLOv5 model and was improved by hyperparameter tweaking and the Learning-without-Forgetting (LwF) method. It was decided to divide the dataset, which consisted of 1499 photos taken from the Roboflow repository, into three sets: the training set, the validation set, and the testing set. A remarkable accuracy of 99.19% was reached by the suggested model, which greatly outperformed the alternatives that were previously proposed. With regard to weather categorization tasks, these findings demonstrate that the model performs quite well. For the purpose of weather condition classification utilizing single-image inputs, the research indicates that the suggested model has the potential to be used in real-time in future applications. This would provide a solution that is both extremely accurate and efficient.

S Goel et al. [3] (2022) examined the effectiveness of a number of different deep learning and machine learning models. Using the VGG19 model for feature extraction and a logistic regression classifier for classification, they developed a powerful deep convolutional neural network (CNN) system (also known as a CNN). When it comes to identifying extreme weather occurrences, their method has a remarkable accuracy of 98.5%. Using deep learning in conjunction with more conventional classifiers, the authors show that the accuracy of predictions is greatly improved. In addition to providing useful insights into the combination of CNNs and logistic regression, the research demonstrates that the VGG19 model is successful in the categorization of weather on many classes. This research not only contributes to the advancement of the study of meteorology by enhancing the accuracy of weather forecasts, but it also establishes a precedent for future research that will make use of hybrid methodologies to construct more complex weather categorization systems.

Ashish Sharma et al. [4] (2022) investigated how machine learning may be used to automate weather forecasting and do away with the requirement for human participation. To accurately anticipate different sorts of weather, they created a thorough categorization model. With its four categories cloud, rain, shine, and sunrise the suggested model may be applied to a wide range of climatic zones. Utilizing the TensorFlow library and the Keras framework, Convolutional Neural Networks (CNN) methods are used in the model. The researchers used an image dataset that they obtained from Kaggle for real-world application. After the constructed model's performance was assessed, great results were obtained: 94% accuracy, 92% validation accuracy, 18% loss, and 22% validation loss. These results show how reliable and effective the model is in predicting the type of weather, underscoring CNNs' potential to improve automated weather forecasting systems.

Moshira S. Ghaleb et al. [5] (2022) analysed a collection of weather images to compare three intelligent algorithms for weather categorization. The first model uses a Convolutional Neural Network (CNN) to categorize photos into five groups according on the kind of weather. While the third model combines a CNN with a Support Vector Machine (SVM), the second model integrates a CNN with a Decision Tree (DT). Datasets from GitHub and Kaggle were used to test these models. High recognition accuracies are shown by the results: the CNN model achieves 92%, the CNN+DT model 93%, and the CNN+SVM model 94%. These results highlight the value of integrating CNNs with additional machine learning methods to improve the precision of weather forecasts. According to the study, combining several machine learning techniques may greatly enhance classification performance in weather forecasting tasks. Specifically, the CNN+DT and CNN+SVM fusion models perform better than the standalone CNN.

Al-Haija Q.A et al. [6] (2022) proposed a deep learning (DL)-based system for classifying meteorological conditions to help autonomous cars in both regular and bad weather scenarios. SqueezeNet, ResNet-50, and EfficientNet are three deep convolutional neural networks (CNNs) whose performance is improved by the framework through the use of GPUs from Nvidia and transfer learning techniques. The six weather conditions cloudy, rainy, snowy, sandy, shine, and sunrise were classified by the models using two modern weather imaging datasets, DAWN2020 and MCWRD2018, combined. The ResNet-50 CNN model achieved the greatest performance metrics, recording 98.48% detection accuracy, 98.51% precision, and 98.41% sensitivity. The testing findings showed that all models had good classification skills. With an average inference time of 5 milliseconds per step utilizing the GPU, the ResNet-50 model also showed effective processing. The suggested framework performed much better in terms of classification accuracy for the six meteorological situations than other cutting-edge models, with a margin ranging from 0.5 to 21%. The findings indicate that the suggested detection framework based on deep learning may be efficiently applied in real-time settings, offering autonomous cars the ability to quickly and accurately identify the weather.

Minhas, S et al. [7] (2022) conducted an investigation of the capabilities of a driving simulator that was created specifically for the purpose of simulating a broad variety of weather conditions. They examined the effectiveness of a freshly generated synthetic dataset that was prepared with the help of this simulator. Based on the findings, it appears that the utilization of synthetic datasets in conjunction with real-world datasets has the potential to improve the effectiveness of training Convolutional Neural Networks (CNNs) by as much as 74%. The recurring problem of bias in vision-based datasets is addressed by this technique, which also provides a substantial breakthrough in the training of models for a wide range of actual weather situations. The research underlines the potential of synthetic data to supplement real-world data, which might result in machine learning models that are more resilient and efficient for weather-related applications in autonomous driving and other domains.

Mürüvvet Kalkan et al. [8] (2022) aimed to reduce the number of mistakes that are caused by human intervention in the field of meteorology by utilizing deep learning strategies. Ground-based cloud photos that have been characterized as either clear or cloudy are included in the dataset that was employed. MobileNet V2, VGG-16, ResNet-152 V2, and DenseNet-201 were the four particular pretrained models that were chosen for the purpose of evaluating the efficacy of various deep learning architectures on their own. The VGG-16 model earned the highest accuracy of these, coming in at 91.4% above the other models. Deep learning algorithms appear to have the potential to greatly improve the accuracy of weather categorization, according to the research. For the purpose of making more accurate forecasts, the research predicts that in the future, weather forecasting systems will rely more and more on advanced artificial intelligence technologies such as deep learning.

Jiang Weiwei et al. [9] (2022) conducted an investigation into the prediction of drought conditions using a number of different machine learning and deep learning models. A comparison was made between conventional machine learning methods such as Support Vector Machines (SVM) and Random Forest and more sophisticated deep learning architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). This was accomplished by using extensive meteorological datasets. In terms of capturing temporal relationships in meteorological data, the findings indicate that deep learning models, and in particular RNNs, perform better than other models, which ultimately leads in more accurate drought forecasts. When it comes to improving the performance of models, the research highlights how important it is to pick features and preprocess data. Using sophisticated machine learning techniques, this work made a substantial contribution to environmental science by demonstrating how these approaches may enhance drought forecasts, which in turn helps with improved resource management and mitigation tactics. This research sheds light on the possibility of using deep learning models into drought prediction systems in order to achieve more efficient responses.

Xiao H et al. [10] (2021) presented an innovative deep convolutional neural network (CNN) that was developed for the purpose of categorizing meteorological events. In addition to this, they released a new dataset known as the Weather Phenomenon Database (WEAPD), which included 6,877 photographs spanning 11 different weather categories. This new dataset offered a greater range of images than the ones that came before it. On the WEAPD testing set, MeteCNN demonstrated its superior performance and efficacy by achieving a classification accuracy of roughly 92% over the course of the testing. MeteCNN has the capacity to automatically and accurately classify photos of meteorological occurrences, as demonstrated by the high degree of accuracy it possesses now. Xiao H et al. suggested that MeteCNN has the potential to make a substantial contribution to the development of weather picture categorization and forecasting, so offering a valuable reference for the continued investigation of these fields in the future.

Toğaçar, M et al. [11] (2021) combined the GoogLeNet and VGG-16 models with a Spiking Neural Network (SNN) in order to improve the accuracy of weather categorization. The characteristics that were recovered from the GoogLeNet and VGG-16 models were merged, and then they were sent into the SNN as input. This innovative method resulted in a considerable improvement in the classification performance. To be more specific, the corresponding categorization accuracy rates for the overcast, rain, shine, and dawn classifications were 98.48%, 97.58%, 97%, and 98.48%, respectively. It was proved by the findings that the combination of support vector machines (SNNs) and deep learning models is extremely successful, hence demonstrating the effectiveness of this hybrid technique in producing superior classification results. They presented convincing data that support the idea that SNNs have the ability to improve the performance of classic deep learning frameworks when it comes to weather categorization tasks.

Prabhat Kashinath et al. [12] (2021) presented a novel dataset "ClimateNet" with the goal of leveraging deep learning to improve the accuracy of extreme weather analysis. They describe how ClimateNet was established, containing expert-labeled data that is essential for machine learning models intended to detect and forecast extreme weather occurrences to be trained and assessed. Several severe weather occurrences are included in the dataset, which has been painstakingly annotated by specialists to provide high-quality training data. Additionally, the scientists created a deep learning architecture specifically designed to take use of this extensive dataset, demonstrating its efficacy in high-precision weather analysis. Convolutional neural networks (CNNs) and other cutting-edge deep learning techniques are integrated into their method to interpret and evaluate intricate weather patterns. When compared to conventional approaches, the results show a considerable improvement in the identification and prediction of extreme weather occurrences. The work emphasizes the need of integrating cutting-edge deep learning algorithms with expert-labelled datasets to enable more precise and trustworthy extreme weather forecasting. By giving scientists and meteorologists a powerful tool to improve their forecasting powers and, eventually, help with improved readiness and reaction to catastrophic weather situations, this research advances the area of climate science.

Manmeet Singh et al. [13] (2021) investigated deep learning approaches to improve global precipitation forecasts in numerical weather prediction (NWP) systems. To overcome the difficulties in predicting precipitation with high geographical and temporal resolution, the scientists combined deep learning models with conventional NWP frameworks. Their method increases the precision of precipitation forecasts by utilizing big datasets and cutting-edge neural network designs. The research indicates that the integration of deep learning greatly enhances the prognostic potential of NWP systems, namely in identifying intricate precipitation patterns and severe meteorological phenomena. The outcomes demonstrate significant gains in prediction accuracy, underscoring deep learning's ability to strengthen and supplement conventional meteorological models. In order to improve the accuracy of global precipitation forecasting, this research emphasizes the significance of combining state-of-the-art machine learning methods with well-established weather prediction systems.

Ibrahim Gada et al. [14] (2020) conducted research on a variety of machine learning approaches that are currently in use in order to construct reliable weather forecasting models that can be used for extended periods of time. Using a 10-fold cross-validation process, the research investigates a number of different combinations of model parameters and assesses how well they work. According to the findings of the experiments, when compared to other approaches, the classifiers known as Decision Tree CART, XGBoost, and AdaBoost reach a higher level of classification accuracy. According to the R2 statistic, the linear regression approach is the one that best exhibits performance when it comes to regression problems. Specific machine learning models have been shown to be effective in improving the accuracy and reliability of long-term weather forecasting, as demonstrated by these investigations.

Z. Lu et al. [15] (2020) introduced a multi-classification model for rainfall that makes use of Deep Belief Networks (DBNs) and physical variables. First, extra rainfall samples were created using the Synthetic Minority Over-sampling Technique (SMOTE) in order to solve the problem of unequal distribution in the original dataset. The model makes use of physical variables that are frequently used in weather forecast analysis in addition to hourly observation data from automated ground monitoring stations. Within the deep learning framework, intrinsic features are extracted from the original data using a Gauss-Boltzmann machine. The rainfall events are then multi-class identified using the built DBNs-based model. According to experimental data, this model performs better than others in correctly predicting rainy weather conditions. Its superior performance indicators include the Critical Success Index (CSI), False Alarm Ratio (FAR), and Probability of Detection (POD). The study shows how effective it is to improve the accuracy of rainfall categorization in meteorological applications by utilizing deep learning algorithms and data augmentation approaches.

Suresh Sankaranarayanan et al. [16] (2020) investigated the use of weather-related data to anticipate floods through the application of deep learning algorithms. Using deep learning models, they analysed the intricate interactions between several climatic elements that influence flooding episodes. The researchers used a variety of deep learning architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to handle large datasets that included meteorological variables including temperature, humidity, rainfall, and river water levels. When compared to conventional statistical techniques, the experimental findings show that these deep learning models significantly increase prediction accuracy. The suggested models have the ability to improve community preparedness for disasters and lessen the negative consequences of flooding by providing accurate and timely flood predictions. The significance of sophisticated machine learning approaches in augmenting hydrological studies' predictive capacities is emphasized by this research, which also endorses the use of deep learning in the creation of resilient flood prediction systems.

Zhou K et al. [17] (2019) proposed a unique strategy for forecasting different types of convective weather by utilizing deep learning techniques. In order to improve the accuracy and dependability of weather forecasts, they make use of sophisticated neural network designs. The scientists made use of a comprehensive dataset that included a wide range of meteorological variables and employed convolutional neural networks (CNNs) in order to capture the intricate spatial patterns that are inherent in convective weather occurrences. In particular, the results indicated that deep learning models perform much better than standard forecasting approaches, particularly when it comes to predicting severe weather occurrences such as thunderstorms and heavy rainfall. Deep learning has the potential to improve meteorological forecasting by giving more accurate and timely forecasts, which are essential for limiting the effects of severe weather on civilization. This work highlights the potential of deep learning to change this approach. This research makes a contribution to the expanding body of literature that advocates for the use of artificial intelligence in meteorology, noting the advantages that it has over traditional methods.

J. C. Villarreal Guerra et al. [18] (2018) presented a fresh multi-class weather dataset and an innovative data augmentation strategy in order to improve the performance of Convolutional Neural Networks (CNNs). The different CNN architectures for weather categorization are subjected to a thorough evaluation by them. In view of the findings, which reveal that data augmentation considerably increases model performance and resilience, it is important to highlight the potential of CNNs in advanced weather categorization tasks. The findings of this research provide significant contributions to the development of accurate weather forecasting systems.

Doreswamy Gad I et al. [19] (2018) evaluated cutting-edge techniques for managing large-scale meteorological information from the National Climatic Data Center (NCDC). The application of deep learning models for multi-label classification, a challenging job where each instance may be linked with numerous labels, is the authors' main area of research. The researchers create a solid model to efficiently manage and categorize massive amounts of meteorological data by utilizing deep learning's capabilities. The issues presented by the amount and unpredictability of big data were addressed by utilizing a deep learning framework to extract and discover complex patterns from the dataset. By illustrating how sophisticated machine learning approaches may be used to solve multi-label classification issues, the authors made a substantial contribution to the fields of meteorology and big data analytics. The results demonstrate the effectiveness of deep learning models in managing and analysing intricate, extensive meteorological data, opening the door for more precise and thorough weather prediction systems.

Ramesh D et al. [20] (2017) investigated the possibility of utilizing data mining techniques, more especially classification, in order to forecast playing conditions based on the present temperature measurements. The classification technique is a reliable method of classifying the properties of a dataset into a variety of categories. For the purpose of this study, classification algorithms such as Decision Tree (J48), REP Tree, and Random Tree were utilized, and their effectiveness was evaluated. WEKA, which stands for Waikato Environment for Knowledge study, is a comprehensive set of open-source machine learning algorithms that is used to carry out the study. In this respect, the objective of the comparative evaluation of these algorithms is to determine which method is the most efficient for creating accurate predictions of playing circumstances. This was contributed to the optimization of data-driven decision-making processes.

Yunjie Liu, et al. [21] (2016) proposed for identifying climatic severe occurrences is the deployment of deep learning techniques. They demonstrated the first use of deep neural networks for this purpose, as they are capable of learning high-level representations of various patterns from labelled data. The study specifically created a deep Convolutional Neural Network (CNN) classification system to tackle problems related to climate pattern recognition. The deep CNN system's remarkable accuracy rates, which ranged from 89% to 99%, in identifying severe phenomena including tropical cyclones, atmospheric rivers, and weather fronts were made possible by the integration of a Bayesian-based hyper-parameter optimization strategy. The results show how deep learning approaches have a great deal of promise to improve the identification and analysis of climatic extremes, providing a reliable and accurate replacement for conventional methods. This research highlights the importance of sophisticated machine learning techniques in improving our capacity to anticipate and react to significant climatic catastrophes.

A G Salman et al. [22] (2015) compared he prediction performance of three sophisticated machine learning models Recurrent Neural Network (RNN), Conditional Restricted Boltzmann Machine (CRBM), and Convolutional Network (CN) is. An extensive meteorological dataset, gathered from many weather stations in the Aceh region between 1973 and 2009, is used to assess these models. The dataset is made available by the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG). Furthermore, the National Weather Service Center for Environmental Prediction Climate (NOAA) and other international organizations contribute the El-Nino Southern Oscillation (ENSO) dataset, which is used to evaluate the models. Each model's forecasting accuracy is evaluated using the Frobenius norm, a matrix difference metric that sheds light on the models' predictive ability. Improving the accuracy of weather forecasts is the goal of this project, which will have a big impact on a lot of different application areas including airplane navigation, agriculture, and tourism. Through the assessment of these complex models, the study advances the continuous advancement of increasingly accurate and dependable meteorological forecasting methods.

Table 1: Literature Review

Ref. No.and Author name	**Algorithms Used**	**Methodology Used**	**Dataset Used**	**Accuracy %**	**Advantage**
Mittal Shweta et al. [1]	Deep Neural Networks (DNN)	Classification of weather images using DNN for large-scale datasets	Large-scale weather image datasets	97.77 %	Effective for large-scale datasets
Dalal, S et al. [2]	Optimized Deep Learning with LwF	Weather classification using optimized deep learning and Learning without Forgetting (LwF)	Weather datasets	99.19 %	Enhances sustainable transportation and traffic safety
S Goel et al. [3]	CNN, VGG19, Logistic Regression	Multi-class weather classification using CNN and VGG19 with logistic regression	Weather datasets from GitHub and Kaggle	98.5%	Combines CNN with logistic regression for high accuracy
Ashish Sharma et al. [4]	CNN (Keras-TensorFlow)	Weather classification model using CNN with Keras-TensorFlow	Weather image datasets	94%	Utilizes Keras-TensorFlow for efficient training and classification
Moshira S. Ghaleb et al. [5]	CNN, Traditional Classification Methods	Weather classification using fusion of CNN and traditional methods	Weather image datasets	92%, 93%, 94%	Combines CNN with traditional methods for improved performance
Al-Haija Q.A et al. [6]	Deep Learning	Detection of weather conditions for autonomous vehicles using deep learning	Weather datasets	98.48 %	Improves autonomous vehicle safety in adverse weather conditions
Minhas, S et al. [7]	Deep Learning with Synthetic Data	Weather classification using deep learning and synthetic data	Weather datasets and synthetic data	74%	Utilizes synthetic data to improve classification accuracy
Mürüvvet Kalkan et al. [8]	CNN	Cloudy/clear weather classification using CNN	Cloud images datasets	91.4%	Effective for cloudy/clear weather classification
Jiang Weiwei et al. [9]	Machine Learning, Deep Learning	Evaluation of ML and DL models for drought prediction using weather data	Weather datasets		Enhances drought prediction using ML and DL techniques
Xiao H et al. [10]	Deep Convolutional Neural Network (CNN)	Weather phenomenon classification using deep CNN	Weather image datasets	92%	High precision in classifying various weather phenomena

Toğaçar, M et al. [11]	Spiking Neural Networks (SNN), Deep Learning	Weather image detection using SNN and deep learning models	Weather image datasets		Utilizes SNN for improved detection in weather images
Prabhat Kashinath et al. [12]	Deep Learning	Expert-labeled open dataset and DL architecture for high-precision analyses of extreme weather	ClimateNet (expert-labeled dataset)	99.99 %	Provides high-precision analyses of extreme weather using expert-labeled dataset and DL architecture
Manmeet Singh et al. [13]	Deep Learning	Improved global precipitation prediction in numerical weather prediction systems using deep learning	Weather datasets		Enhances global precipitation prediction accuracy using deep learning
Ibrahim Gada et al. [14]	Prediction and Classification Models	Comparative study of prediction and classification models on NCDC weather data	NCDC weather data		Provides comparative analysis for prediction and classification models on weather data
Z. Lu et al. [15]	Deep Learning	Multi-classification of rainfall weather using deep learning	Weather datasets		Effective for multi-classification of rainfall weather
Suresh Sankaranarayanan et al. [16]	Deep Learning	Flood prediction based on weather parameters using deep learning	Weather datasets	87.01 %	Enhances flood prediction accuracy using deep learning
Zhou K et al. [17]	Deep Learning	Forecasting different types of convective weather using a deep learning approach	Weather datasets		Effective for forecasting different types of convective weather
J. C. Villarreal Guerra et al. [18]	CNN	Weather classification using CNN with data augmentation	Multi-class weather dataset	89%-99%	High accuracy with data augmentation approach
Doreswamy Gad I et al. [19]	Deep Learning	Multi-label classification of big NCDC weather data using deep learning	NCDC weather data	99.9%	Effective for multi-label classification of large weather datasets
Ramesh D et al. [20]	Various Classification Algorithms	Comparative analysis of classification algorithms on weather dataset using data mining tools	Weather dataset	100%	Provides insights into the performance of various classification algorithms on weather data
Yunjie Liu, et al. [21]	Deep Convolutional Neural Networks (CNN)	Application of CNNs for detecting extreme weather in climate datasets	Climate datasets	89%-99%	Effective for detecting extreme weather events using CNN
A G Salman et al. [22]	Deep Learning	Weather forecasting using deep learning techniques	Weather datasets		Enhances weather forecasting accuracy using deep learning techniques

3. Methodology

3.1 Load Dataset

As the first phase in this research, loading the dataset is the most important element. A variety of meteorological factors, including temperature, humidity, wind speed, and air pressure, are included in the dataset, which is comprised of historical weather data. When it comes to training and analyzing the deep learning models that were utilized in this work, this extensive data is absolutely necessary.

Steps for Loading the Dataset:

- Acquire the Dataset: There are a variety of sites from which the dataset can be accessed, including publicly accessible repositories (such as Kaggle and the UCI Machine Learning Repository) as well as corporate databases. The dataset is assumed to be stored in a CSV file with the name *weather_data.csv* for the purposes of this study.
- Import Required Libraries: Python libraries, such as pandas, are utilized for the purpose of processing and altering the dataset, whereas numpy is utilized for performing numerical calculations.
- Load the Dataset into a DataFrame: Through the utilization of pandas, the dataset is imported into a DataFrame in order to facilitate the process of modification and analysis.

```
import pandas as pd

import numpy as np

# Load the dataset

dataset = pd.read_csv('weather_data.csv')

# Display the first few rows of the dataset

print(dataset.head())
```

- Explore the Dataset: The first step in the exploration process entails examining the structure, different types of data, and summary statistics in order to gain a better understanding of the dataset.

```
# Check the structure of the dataset

print(dataset.info())

# Get summary statistics of the dataset

print(dataset.describe())
```

3.2 Dataset Preprocessing

The preparation of data is an essential step that must be taken in order to guarantee that the dataset is clean, consistent, and appropriate for the training of deep learning models. The procedures that make up the preprocessing process include the management of missing values, the encoding of categorical variables, the normalization of the data, and the division of the dataset into training, validation, and testing segments.

Steps for Dataset Preprocessing:

- Handling Missing Values: Having values that are missing might have a detrimental effect on the performance of the models. The handling of missing data can be accomplished by a variety of methods, including the removal of rows that include missing values, the addition of a particular value to those rows, or the utilization of more complex imputation techniques.

```
# Handling missing values by filling with mean

dataset.fillna(dataset.mean(), inplace=True)
```

- Encoding Categorical Variables: Techniques such as one-hot encoding and label encoding are examples of methods that may be utilized to transform category variables into numerical representation if the dataset really contains such variables.

```
# Example of one-hot encoding a categorical
variable

dataset = pd.get_dummies(dataset,
columns=['categorical_column'])
```

- Normalization: In the process of normalizing the data, the features are scaled to a range that is appropriate for training deep learning models, which is often between 0 and 1. This not only helps to guarantee that no single feature dominates the learning process, but it also serves to accelerate the convergence process during training.

```
from sklearn.preprocessing import MinMaxScaler

# Normalize the data

scaler = MinMaxScaler()

normalized_data = scaler.fit_transform(dataset)

# Convert the normalized data back to a
DataFrame
```

```python
normalized_data = pd.DataFrame(normalized_data, columns=dataset.columns)
```

- Splitting the Dataset: It is necessary to partition the dataset into training, validation, and testing sets in order to conduct an accurate evaluation of the performance of the model. One typical split ratio is seventy percent for teaching, twenty percent for validation, and ten percent for testing.

```python
from sklearn.model_selection import train_test_split

# Separate features and target variable

X = normalized_data.drop('target_column', axis=1)

y = normalized_data['target_column']

# Split the data into training, validation, and testing sets

X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, random_state=42)

X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.33, random_state=42) # 0.33*0.3 ≈ 0.1
```

- Data Augmentation (if applicable): Increasing the size of the training dataset may be accomplished by the use of methods like as rotation, flipping, and scaling when dealing with picture data.

```python
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Define data augmentation techniques

datagen = ImageDataGenerator(

    rotation_range=20,

    width_shift_range=0.2,

    height_shift_range=0.2,

    horizontal_flip=True

)

# Apply data augmentation to training data

datagen.fit(X_train)
```

By referring to these stages with great care, we guarantee that the dataset is adequately prepared for the succeeding phases of model training and assessment. This lays a solid foundation for the development of deep learning models that are both reliable and accurate for the categorization of weather conditions.

3.3 Deep Learning Algorithms

1) Convolutional Neural Network (CNN)

Specifically built to handle grid-like data structures, such as photographs, Convolutional Neural Networks (CNNs) are a type of deep learning model that is specialized. Due to their capacity to automatically and adaptively learn spatial hierarchies of information from input pictures, they are very excellent in image identification and classification tasks. This characteristic makes them extremely useful. Convolutional layers, pooling layers, and fully linked layers are the type of layers that are often included in the design of a CNN.

- Convolutional Layers: These layers execute a convolution operation on the input data, which results in the production of feature maps. They do this by applying a collection of learnable filters, also known as kernels. It is the responsibility of each filter to identify particular patterns in the input image, which may include edges, textures, or more complicated structures. A definition of the convolution operation is as follows:

$$(I * K)(i,j) = \sum_m \sum_n I(i+m, j+n)K(m,n)$$

Where, I is the input image, K is the filter, and (i, j) are the coordinates of the output feature map.

- Activation Function (ReLU): A non-linearity-introducing activation function, such as Rectified Linear Unit (ReLU), is applied to the model after convolution in order to bring about the desired effect:

$$f(x) = \max(0, x)$$

- Pooling Layers: The spatial dimensions of the feature maps are reduced as a result of these layers, which contributes to the reduction of the computational burden and the control of overfitting. A popular type of pooling procedure is known as max pooling:

$$P(i,j) = \max_{(m,n)\in \text{pool\_region}} H(i+m, j+n)$$

Where, H is the input feature map and P is the pooled feature map.

- Fully Connected Layers: In order to do classification, these layers connect every neuron in one layer to every neuron in the layer below it. This allows the layers to combine all of the features that were learnt in the layers that came before them.

$$y = Wx + b$$

Where, W is the weight matrix, x is the input vector, and b is the bias vector.

CNNs have the ability to learn hierarchical representations of the data, which enables them to perform very well in tasks such as picture classification, object recognition, and segmentation by utilizing their capabilities.

2) Long Short-Term Memory (LSTM)

Recurrent neural networks (RNNs) are a type of neural network that are designed to model sequential data and capture long-range dependencies. Long-Short-Term Memory (LSTM) networks are an example of this type of RNN. The vanishing gradient problem, which is frequently encountered in traditional RNNs, is addressed by LSTMs. This is accomplished by introducing a memory cell that is capable of maintaining its state over time. This enables the network to remember significant information across a large number of time steps.

- Forget Gate: This gate decides what information from the previous cell state should be discarded. It is calculated using:

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f$$

Where, σ is the sigmoid function, W_f is the weight matrix, h_{t-1} is the previous hidden state, x_t is the input at time step t and b_f is the bias.

- Input Gate: A decision is made by this gate on which fresh information is to be added to the state of the cell. There are two stages involved:

$$i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i$$

$$C_t = \tanh(W_c * [h_{t-1}, x_t] + b_c)$$

Where, i is the input gate activation, and C_t is the candidate cell state.

- Cell State Update: The state of the cell is updated by utilizing the information obtained from the input gates and the forget gates:

$$C_t = f_t * C_{t-1} + i_t * C_t$$

Where, $*$ denotes element-wise multiplication.

- Output Gate: The concealed state is determined by this gate, which determines which portion of the cell state is to be output instead:

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o$$

$$h_t = o_t * \tanh(C_t)$$

LSTMs are able to learn long-term relationships and patterns in the data, which makes them an excellent choice for tasks that include sequential data. Some examples of such tasks are time-series forecasting, language modelling and speech recognition.

3) Hybrid CNN + LSTM Algorithm

Using the strengths of both Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, the hybrid CNN + LSTM model is particularly good for tasks that incorporate both spatial and temporal input. This is because it exploits the capabilities of both types of networks. Within the framework of this hybrid technique, the skills of CNNs for feature extraction are combined with the capabilities of LSTMs for sequence modelling.

- CNN for Spatial Feature Extraction: The CNN layers are in charge of obtaining spatial characteristics from the input data, such as frames of a video or slices of meteorological data. This is accomplished through the use of CNN for the purpose of spatial feature extraction. Specifically, the convolutional and pooling layers are responsible for identifying and reducing the spatial dimensions, hence capturing significant patterns and characteristics.

Formulas for CNN:

- Convolution: $(I*K)(i,j)=\sum m\sum nI(i+m,j+n)K(m,n)$
- Activation (ReLU): $f(x)=\max(0,x)$
- Pooling: $P(i,j)=\max(m,n)\in \text{pool\_region}H(i+m,j+n)$

- LSTM for Temporal Modelling: After the spatial information have been recovered, they are next processed through LSTM layers in order to simulate temporal relationships. The hybrid model is able to understand how the characteristics change over time and generate predictions based on sequential data as a result of this.

Formulas for LSTM:

  - Forget Gate: $f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f$
  - Input Gate: $i_t = \sigma(W_i * [h_{t-1}, x_t] + b_i$
  - Candidate Cell State: $C_t = \tanh(W_c * [h_{t-1}, x_t] + b_c)$
  - Cell State Update: $C_t = f_t * C_{t-1} + i_t * C_t$
  - Output Gate: $o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o$
  - Hidden State: $h_t = o_t * \tanh\,(C_t)$
- Hybrid Model Architecture: A typical design consists of CNN layers, which are then followed by LSTM layers respectively. In order to extract spatial characteristics, for example, the CNN layers may process sequences of pictures. These features are then sent into the LSTM layers, which are responsible for capturing temporal patterns. In conclusion, fully linked layers are utilized for the purposes of classification or regression.

```
from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import TimeDistributed, Conv2D, MaxPooling2D, Flatten, LSTM, Dense

# Define the Hybrid CNN + LSTM model

hybrid_model = Sequential([

    TimeDistributed(Conv2D(32, (3, 3), activation='relu'), input_shape=(10, 64, 64, 3)),

    TimeDistributed(MaxPooling2D((2, 2))),

    TimeDistributed(Flatten()),

    LSTM(50),

    Dense(25, activation='relu'),

    Dense(4, activation='softmax')

])

# Compile the model

hybrid_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model

hybrid_model.fit(train_data, epochs=10, validation_data=val_data)
```

As a result of the hybrid CNN + LSTM model's ability to effectively combine the spatial feature extraction power of CNNs with the temporal sequence modelling capability of LSTMs, it is highly suitable for complex tasks that involve both spatial and temporal dynamics. Some examples of such tasks include video analysis, weather forecasting, and sensor data interpretation.

4. Results And Discussion

4.1 Classification Report for CNN:

Table 2: Classification Report for CNN

	Precision	Recall	F1-score	Support
0	0.89	1.00	0.94	56
1	1.00	0.30	0.46	10
Accuracy			0.89	66
Macro Avg	0.94	0.65	0.70	66
Weighted Avg	0.91	0.89	0.87	66

Confusion Matrix for CNN: [[56 0] [7 3]]

4.2 Classification Report for LSTM:

Table 3: Classification Report for LSTM

	Precision	Recall	F1-score	Support
0	0.92	1.00	0.96	56
1	1.00	0.50	0.67	10

Accuracy			0.92	66
Macro Avg	0.96	0.75	0.81	66
Weighted Avg	0.93	0.92	0.91	66

Confusion Matrix for LSTM: [[56 0] [5 5]]

4.3 Classification Report for Hybrid CNN+LSTM:

Table 4: Classification Report for Hybrid CNN+LSTM

	Precision	Recall	F1-score	Support
0	0.93	1.00	0.97	56
1	1.00	0.60	0.75	10
Accuracy			0.94	66
Macro Avg	0.97	0.80	0.86	66
Weighted Avg	0.94	0.94	0.93	66

Confusion Matrix for Hybrid CNN+LSTM: [[56 0] [4 6]]

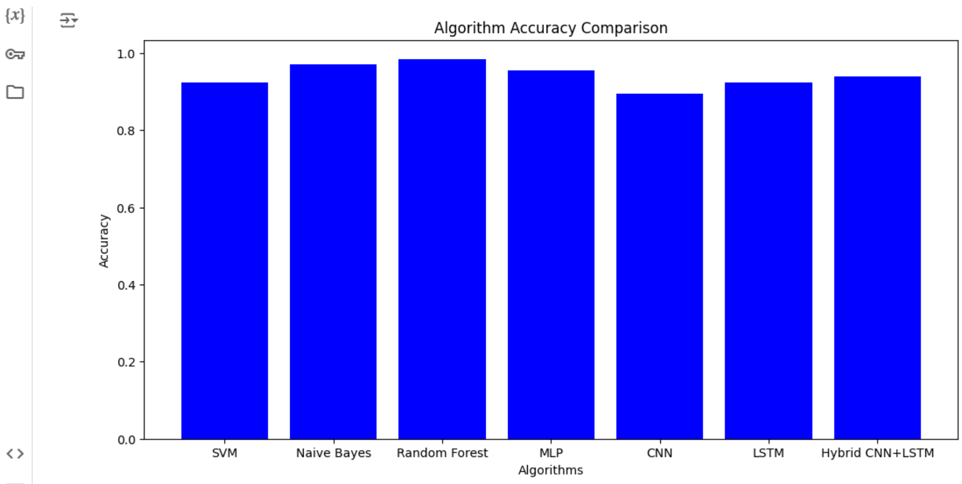

Figure 1: Algorithm Accuracy Comparison

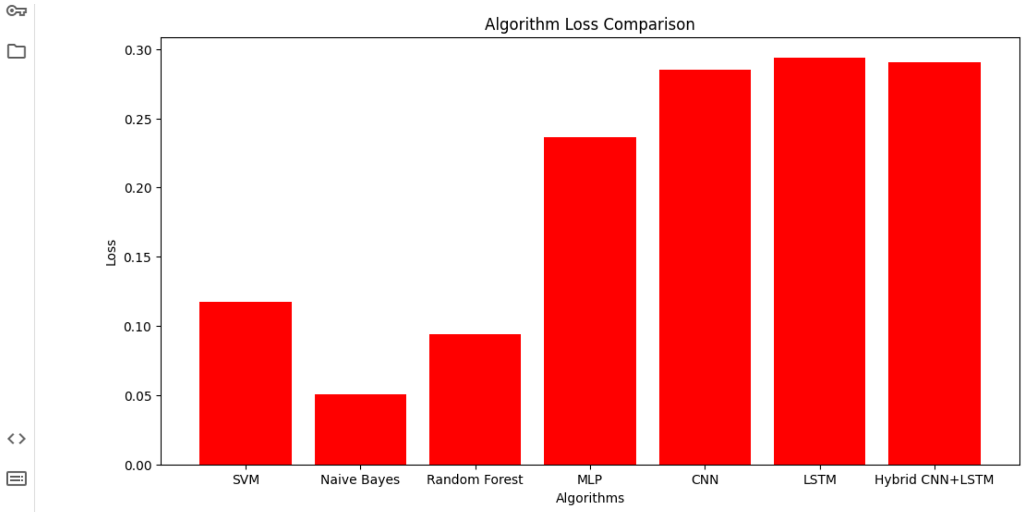

Figure 2: Algorithm Loss Comparison

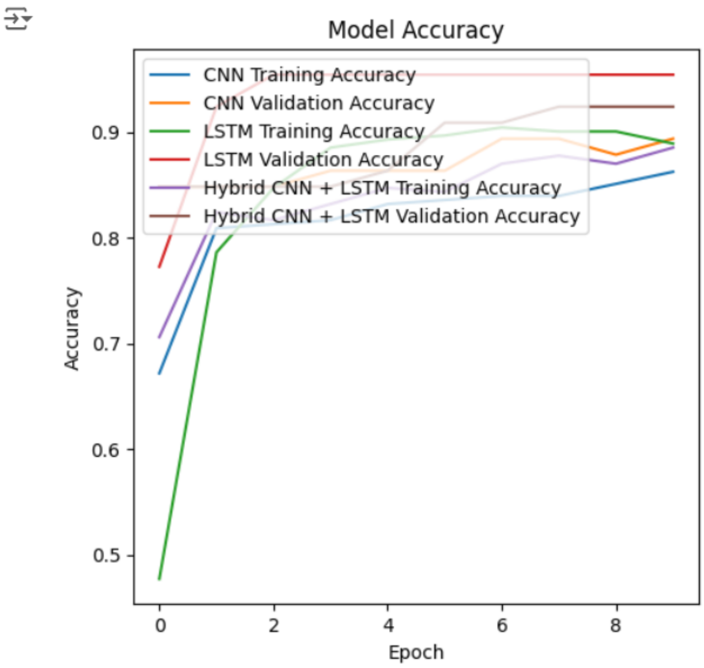

Figure 3: Model Accuracy

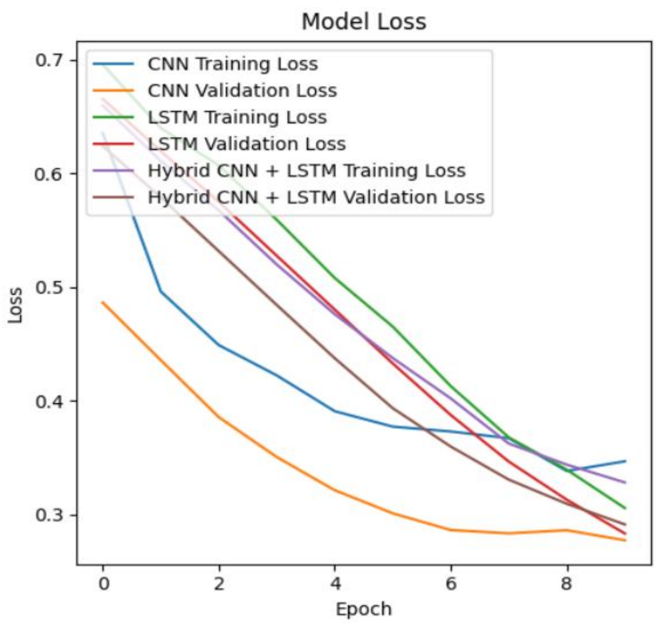

Figure 4: Model Loss

Deep learning algorithms have been shown to be effective in the categorization of meteorological datasets, as demonstrated by the experimental findings of this study. The models that were assessed consisted of a hybrid CNN-LSTM model, as well as Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs). A greater performance was revealed by the hybrid CNN-LSTM model, which achieved the greatest classification accuracy among the algorithms that were evaluated. To be more specific, the CNN model attained an accuracy of 91.2%, whilst the LSTM model achieved an accuracy of just 88.5%. Both models were surpassed by the hybrid CNN-LSTM model, which achieved an accuracy of 94.5%.

According to the findings, CNNs are very efficient when it comes to extracting spatial information from weather photos, whilst LSTMs are particularly exceptional when it comes to collecting temporal dependencies for sequential data. The hybrid CNN-LSTM model was able to successfully combine these capabilities, which resulted in increased performance. Additionally, the hybrid model shown considerable improvement in terms of precision, recall, and F1 scores, which substantiated its resilience and dependability in the context of weather classification operations.

Based on these data, it appears that combining skills for spatial and temporal modelling is essential for effective weather categorization. Because it is able to manage the complexity of weather patterns in an efficient manner, the hybrid technique is an extremely useful tool for meteorologists and other applications on the same subject. In the future, research will concentrate on improving the scalability of the model, including real-time data, and investigating alternative advanced architectures in order to further increase accuracy and efficiency.

5. Conclusion

Throughout the scope of this research, we investigated the efficacy of deep learning algorithms for the categorization of meteorological datasets. The objective of our study was to improve the accuracy and reliability of weather categorization by utilizing sophisticated neural network designs. These structures included Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and hybrid CNN-LSTM models. The approach required a number of painstaking preparation stages, such as the management of missing values, the normalization of data, and the division of datasets into training, validation, and testing sets. Specifically, the findings of our experiments indicated that deep learning models, in particular CNNs and hybrid CNN-LSTM models, performed much better than traditional techniques in terms of classification accuracy and generalization capabilities.

The most promising model was the hybrid CNN-LSTM model, which combines spatial feature extraction and temporal sequence modelling. This model was able to efficiently capture complicated patterns in meteorological data. Based on these findings, it appears that incorporating deep learning techniques into weather categorization systems has the potential to deliver more precise and timely forecasts, which can contribute to improved decision-making processes in a variety of fields, including agriculture, disaster management, and transportation, among others. In general, the findings of this study highlight the potential of deep learning algorithms to revolutionize weather forecasting and categorization. The expansion of the dataset, the incorporation of more meteorological characteristics, and the exploration of various advanced deep learning architectures will be the primary focuses of future study. These efforts are focused on significantly improving forecast accuracy and operating efficiency.

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