

WEATHER CLASSIFICATION USING DEEP LEARNING

Project Report

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering Degree in Electronics and Communication Engineering

by

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**DEPARTMENT OF ELECTRONICS AND COMMUNICATION
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SCHOOL OF ELECTRICAL AND ELECTRONICS

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

**Accredited with Grade “A++” by NAAC | 12B Status by UGC |
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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **PAVITHRA S (40130169)** who carried out the project entitled "**WEATHER CLASSIFICATION USING DEEP LEARNING**" under my supervision from November 2023 to April 2024.

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I, PAVITHRA S (40130169) hereby declare that the Project report entitled "WEATHER CLASSIFICATION USING DEEP LEARNING" done by me under the guidance of Dr. P. CHITRA, M.E., Ph.D., is submitted in partial fulfillment of the requirements for the award Bachelor of Engineering Degree in DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING.

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ABSTRACT

Weather classification plays a crucial role in various applications, including environmental monitoring, agriculture, and disaster management. In this research, we provide comprehensive approach for multiclass weather image classification utilizing deep learning models, namely Convolutional Neural Networks (CNN), VGG16, GoogLeNet, and AlexNet. The dataset used for training and evaluation comprises diverse weather conditions, including sunny, cloudy, rainy, and snowy scenes. We fine-tune pre-trained models on this dataset to leverage their feature extraction capabilities effectively. Extensive experiments are conducted to compare the performance of the deep learning architectures in terms of accuracy, precision, recall, and F1-score. Additionally, we investigate the robustness of the models against variations in weather conditions and lighting conditions. Our results demonstrate the effectiveness of deep learning models in accurately classifying multiclass weather images, with certain architectures exhibiting superior performance over others. This research contributes to the advancement of weather classification systems, which can aid in various real-world applications requiring accurate and timely weather information.

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LIST OF ABBREVIATIONS

DNN	Deep Neural Networks
CNN	Convolution Neural Network
MWD	Multi-class Weather Dataset
VGG	Visual Geometry Group
AI	Artificial Intelligence
DLWP	Deep Learning-based Weather Prediction
NN	Neural Network
NWP	Numerical Weather Prediction
LwF	Learning-without-Forgetting
SNN	Spiking Neural Network
ANN	Artificial Neural Network
SIANN	Space Invariant or Shift Invariant Artificial Neural Networks
ReLU	Rectified Linear Unit

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CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Weather classification is an essential task in meteorology and has numerous applications ranging from disaster management to agricultural planning. Traditional methods of weather classification often rely on manual observation and interpretation, which can be time-consuming and subjective. With the advent of deep learning algorithms, particularly Convolutional Neural Networks (CNNs), significant strides have been made in automating weather classification processes.

In this study, we focus on employing deep learning algorithms such as CNN, VGGNet, GoogLeNet, and AlexNet for multi-class weather classification. CNNs have demonstrated remarkable success in various image classification tasks, making them a natural choice for weather classification due to their ability to automatically learn features from raw input data. VGGNet, GoogLeNet, and AlexNet are well-known deep learning architectures that have shown superior performance in image classification tasks, and we aim to evaluate their effectiveness in the context of weather classification.

Our primary objective is to assess the accuracy, precision, recall, and F1-score of these deep learning models in classifying different weather conditions. Accuracy measures the overall correctness of the classification, while precision quantifies the ratio of correctly predicted instances of a class to the total predicted instances of that class. Recall, also known as sensitivity, measures the ability of the model to identify all relevant instances of a class. F1-score provides a balance between precision and recall, offering a single metric to evaluate the model's performance.

By comparing the performance of CNN, VGGNet, GoogLeNet, and AlexNet on a multi-class weather classification task, we aim to identify the most effective architecture for this specific application. Additionally, we will explore the impact of factors such as dataset size, image resolution, and preprocessing techniques on the performance of these models.

This research is significant as it not only contributes to the advancement of automated weather classification techniques but also has practical implications for various sectors such as agriculture, transportation, and disaster response. Accurate

and timely weather classification can facilitate informed decision-making and improve preparedness in response to changing weather conditions, ultimately enhancing societal resilience to weather-related challenges.

In summary, this study aims to leverage deep learning algorithms to automate multi-class weather classification and evaluate the performance of CNN, VGGNet, GoogLeNet, and AlexNet in terms of accuracy, precision, recall, and F1-score. The findings of this research will contribute to the development of robust and reliable systems for automated weather classification, with potential applications across diverse domains.

1.2 IMAGE RECOGNITION

Based on how humans identify items in various sets of images, image recognition is a process used to detect an object within an image and classify it in a given category.

Identifying, labeling, and classifying objects that are identified into several categories is the aim of image recognition. The entire process of object or image recognition includes a number of conventional computer vision tasks, such as:

- Classifying images: Assigning labels and establishing groups.
- Object detection: Using bounding boxes to detect the existence of objects and classify them according to their class membership.

This computer vision job has shown significant progress in the last few years, primarily due to deep learning applications.

The machine must first be aware of precisely what it needs to search for. As a result, it needs to be given the guidelines that have been decided upon. It's critical to provide the sizes of the bounding boxes and the components inside. The machine needs some references, such as images, videos, photos, etc., in order to accomplish this. It will be able to analyze future data more effectively because to these components. This will create a sort of data library that will then be used by the deep learning models to distinguish the various objects. A Neural Network is composed of multiple artificial neurons. Neurons are designed to mimic brain activity in humans. It operates using a range of different algorithms that are also modeled after how the brain works.

Second, the model needs to go on a training phase. The dataset needs to be entered within a program in order to function properly. And this phase is only meant to train the deep learning models to identify specific objects and organize them accurately in the correspondent classes.

An AI model must undergo extensive testing prior to being put to use. In order to accomplish this, pictures that weren't included in the training phase must be proposed. The model will be accepted or rejected based on the program's ability to recognize every item and the precision of the categorization.

1.3 DEEP NEURAL NETWORK

Among the tasks that deep neural networks (DNNs) excel at is image recognition. Computer systems with neural networks are made to identify patterns. Their construction takes its cues from the structure of the human brain, thus the name. There are three different kinds of layers in them: input, hidden layers, and output. A signal is received by the input layer, processed by the hidden layer, and then a decision or forecast regarding the input data is made by the output layer. The computational work is done by interconnected nodes, or artificial neurons, at each network layer.

A high number of hidden layers comprise a neural network. Deep networks may feature hundreds of hidden layers, compared to the three seen in standard neural networks.

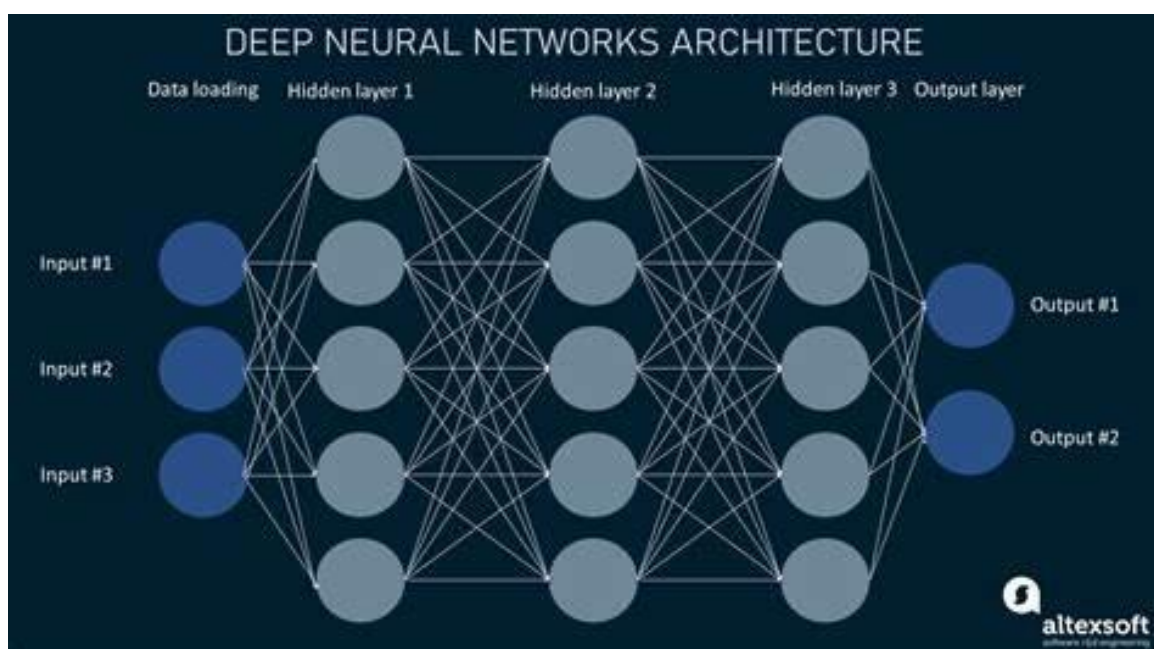


Fig 1.1 The architecture of neural network

1.4 DATASET

A carefully selected collection of digital photos is called a dataset in computer vision, and it is used by programmers to test, train, and assess the functionality of their algorithms. It is claimed that the algorithm picks up knowledge from the dataset's instances. Items would be identified and called out, etc. Therefore, a dataset in computer vision gathers a series of labeled photos that are used to "point things out" and name items in the real world.

The dataset which will be used for training and testing this model are collected by researchers. Below are some samples of Multi-class Weather Images:



Fig 1.2 Cloudy



Fig 1.3 Rainy



Fig 1.4 Sunshine



Fig 1.5 Sunrise

This dataset comprises a diverse collection of weather images, totaling 1125 instances, meticulously curated to represent a variety of weather conditions encountered in the natural environment. Each image is annotated with one of four distinct weather classes: cloudy, rainy, sunshine, and sunrise, offering a comprehensive representation of meteorological phenomena. Upon analysis, it is observed that the dataset exhibits a distribution of weather classes as follows: approximately 26.67% of the images depict cloudy conditions, while rainy weather is represented in 19.11% of the dataset. Sunshine, characterized by clear skies and abundant sunlight, constitutes approximately 22.49% of the dataset. Finally, the sunrise class accounts for the largest proportion, comprising 31.73% of the total images, capturing the ethereal beauty of the early morning landscape.

1.5 PROBLEM STATEMENT

Accurate weather classification have been extensively classified for weather forecasting. However, existing methods often rely on manual visual observations or lack the ability to distinguish multiple weather phenomena efficiently. The challenge lies in developing an automated and high-quality system that can classify weather conditions (such as sunrise, shine, rain, and cloudy) accurately using deep learning techniques. This research aims to address this problem by proposing novel deep learning architectures and creating an extended weather phenomenon dataset. The goal is to achieve superior classification performance while considering computational efficiency and real-world deployment.

1.6 OBJECTIVE

In this project, our aim is to employ deep learning techniques to classify multi-class weather based on a carefully curated dataset. We intend to utilize various pre-defined deep learning models, such as Convolutional Neural Networks (CNNs), VGGNet, GoogLeNet, and AlexNet, to perform the classification task. Various pre-defined deep learning models will be used to classify the dataset and these models will be compared against each other in order to choose the most effective model. The primary objective is to compare the performance of these models against each other, evaluating metrics such as accuracy, precision, recall, and F1-score, in order to identify the most effective model for weather classification. By leveraging state-of-the-art deep learning architectures and comprehensive evaluation criteria, we seek to enhance our understanding of the capabilities of these models in accurately categorizing diverse weather conditions. This comparative analysis will not only inform our selection of the optimal model but also contribute valuable insights to the broader field of weather prediction and classification using deep learning methodologies.

CHAPTER 2

LITERATURE SURVEY

2.1 INFERENCES FROM LITERATURE SURVEY

This chapter deals with all the inferences from the literature survey.

Guerra et al. (2018) created a new open source dataset consisting of images depicting three classes of weather i.e rain, snow and fog called RFS Dataset. A novel algorithm has also been proposed which has used super pixel delimiting masks as a form of data augmentation, leading to reasonable results with respect to ten Convolutional Neural Network architectures [4].

Jaseena et al. (2022) provided an extensive review of weather forecasting models and various techniques and methodologies currently used by various researchers for weather forecasting. The main highlights of the paper are presented below. (1) A comprehensive review of various weather forecasting models. (2) Analysis of the essential hyper-parameters used by the forecasting models. (3) A precise classification of various weather forecasting models. (4) Exploration of the effectiveness of the various models using statistical error indicators [5].

Zenkner et al. (2023) examined deep learning to forecast weather given historical data from two London-based locations. Two distinct Bi-LSTM recurrent neural network models were developed in the TensorFlow deep learning framework and trained to make predictions in the next 24 and 72 h, given the past 120 h. The first trained neural network predicted temperature at Kew Gardens with a forecast accuracy of $\pm 2^\circ\text{C}$ in 73% of instances in a whole unseen year, and a root mean squared errors of 1.45°C . The second network predicted 72-h air temperature and relative humidity at Heathrow with root mean squared errors 2.26°C and 14% respectively and 80% of the temperature predictions were within $\pm 3^\circ\text{C}$ while 80% of relative humidity predictions were within $\pm 20\%$. Both networks were trained with five years of historical data, with cloud training times of over a minute (24-h network) and three minutes (72-h) [14].

Ren et al. (2021) focused on how Deep learning-based weather prediction (DLWP) is expected to be a strong supplement to the conventional method. At present, many researchers have tried to introduce data-driven deep learning into weather forecasting, and have achieved some preliminary results. In this paper, we survey the state-of-the-art studies of deep learning-based weather forecasting, in the aspects of the design of neural network (NN) architectures, spatial and temporal scales, as well as the datasets and benchmarks. Then we analyze the advantages and disadvantages of DLWP by comparing it with the conventional NWP, and summarize the potential future research topics of DLWP [13].

Wang et al. (2018) proposed a novel method for multi-class weather classification. We newly constructed multi-class weather dataset contains 5K images which has more adverse weather conditions. To improve the discrimination of image representation and decrease the influence of pre-processing, our approach combines the real-time weather data with the image feature as the final feature vector to identify different weather. With experiments on our own dataset, we demonstrate that the proposed framework achieves superior performance compared to the state-of-the-art methods [12].

Goel et al. (2022) proposed deep learning techniques are used as an alternate tool for identifying extreme weather occurrences. From labelled data, deep neural networks can develop high-level representations of a wide range of patterns. In this work, we have created a deep convolutional neural network (CNN) classification system. Our deep CNN system detects extreme events with VGG19 model and logistic regression classifier with 98.5% accuracy [8].

Al-Haija et al. (2020) proposed an accurate and precise self-reliant framework for weather recognition using ResNet-18 convolutional neural network to provide multi-class weather classification. The proposed model employs transfer learning technique of the powerful ResNet-18 CNN pretrained on ImageNet to train and classify weather recognition images dataset into four classes including: sunrise, shine, rain, and cloudy. The simulation results showed that our proposed model

achieves remarkable classification accuracy of 98.22% outperforming other compared models trained on the same dataset [7].

Dalal et al. (2023) developed a good weather classifier that uses only a single image as input. To resolve quality-of-life challenges, we propose a modified deep-learning method to classify the weather condition. The proposed model is based on the YOLOv5 model, which has been hyperparameter tuned with the Learning-without-Forgetting (LwF) approach. We took 1499 images from the Roboflow data repository and divided them into training, validation, and testing sets (70%, 20%, and 10%, respectively). The proposed model has gained 99.19% accuracy. The results demonstrated that the proposed model gained a much higher accuracy level in comparison with existing approaches. In the future, this proposed model may be implemented in real-time [2].

Gupta et al. (2023) presented an approach for multi-class weather classification by harnessing the power of deep learning techniques and transfer learning. The research utilizes the Multi-class Weather Dataset (MWD[20]), comprising four weather conditions: sunrise, shine, rain, and cloudy. Using pre-trained deep learning architectures such as ResNet50, Densenet-161, InceptionV3, VGG19, and MobileNet, the present research extracts intricate features from the dataset images. Also, Transfer learning is employed to fine-tune these models for weather classification, effectively addressing the constraints posed by a scarcity of labeled data. The role of a logistic regression model is pivotal as the multi-class classifier. In-depth evaluation metrics encompassing accuracy, precision, recall, and F1 score are employed, accompanied by a meticulous analysis utilizing confusion matrix techniques. The results show that Densenet-161 demonstrates superior performance while other models exhibit competitive results presenting viable alternatives for specific use cases. Overall, the study contributes insights into the effectiveness of pre-trained models and transfer learning in multi-class weather classification tasks [1].

Salman et al. (2015) introduced a novel framework to automatically extract this information from street-level images relying on deep learning and computer vision using a unified method without any pre-defined constraints in the processed

images. A pipeline of four deep Convolutional Neural Network (CNN) models, so-called the WeatherNet, is trained, relying on residual learning using ResNet50 architecture, to extract various weather and visual conditions such as Dawn/dusk, day and night for time detection, and glare for lighting conditions, and clear, rainy, snowy, and foggy for weather conditions. The WeatherNet shows strong performance in extracting this information from user-defined images or video streams that can be used not limited to: autonomous vehicles and drive-assistance systems, tracking behaviours, safety related research, or even for better understanding cities through images for policy-makers [3].

Kalkan et al. (2022) aimed to reduce human-induced meteorology errors as much as possible with the application of deep learning techniques. The dataset that was preferred contains cloud pictures taken from the ground which are classified as either clear or cloudy. In order to compare different deep learning architectures and their efficiency on this subject, four particular pretrained models were selected. Among the models based on MobileNet V2, VGG-16, ResNet-152 V2, DenseNet-201: VGG-16 came as the best in terms of accuracy with 91.4%. In the future, it can be foreseen that all weather forecasting systems will prefer making their predictions based on modern artificial technologies like deep learning [6].

Togacar et al. (2021) used a dataset in the study which has four classes: cloudy, rain, shine, and sunrise. In the study, GoogLeNet and VGG-16 models and the spiking neural network (SNN) were used together. The features extracted from GoogLeNet and VGG-16 models were combined and given to the SNNs as the input. As a result, the SNNs contributed to the success of classification with the proposed approach. The classification accuracy rates of cloudy, rain, shine, and sunrise classes were 98.48%, 97.58%, 97%, and 98.48%, respectively, together with SNN. Also, the use of SNNs in combination with deep learning models to obtain a successful result is proved in this study [11].

Sharma et al. (2022) provided a base to examine the weather through the machine without human intervention. This study offers a thorough classification model to forecast a weather type. Here, the model facilitates defining the best results for the weather prediction model to any climatic zones and categorizes the climate

into four types: cloud, rain, shine, and sunrise. This model designs and reveals using convolution neural networks (CNN) algorithms with Keras framework and TensorFlow library. For practical implementations, use the images dataset available from the kaggle.com website. As a result, this research presents the performance of the designed and developed model. It shows accuracy, validation accuracy, losses, and validation losses approximately 94%, 92%, 18%, and 22%, respectively [10].

Chandrashaker et al. (2017) surveyed many Statistical and Predictive models for rainfall forecasting system available in the literature. These models provided less accuracy prediction models in large- scale rainfall forecasting (Yearly basis) due to the dynamic temperament of climate conditions. Weather damage prediction is an important research issue where it relates, both science and technology in order to forecast the weather damage of a particular location. We have a many good prediction system but there is no proper estimation for future damage because the time span between the present moment and time for which forecasting is being made and released is varied. By collecting previous datasets from data centers like India Meteorological Departments in a specific location and using regression analysis, we can predict (numerical data) the values of damage. In this paper we mainly discuss about the various weather predictions models proposed by different researchers [14].

Haixia et al. (2021) stated Weather phenomenon recognition notably affects many aspects of our daily lives, for example, weather forecast, road condition monitoring, transportation, agriculture, forestry management, and the detection of the natural environment. In contrast, few studies aim to classify actual weather phenomenon images, usually relying on visual observations from humans. To the best of our knowledge, the traditional artificial visual distinction between weather phenomena takes a lot of time and is prone to errors. Although some studies improved the recognition accuracy and efficiency of weather phenomenon by using machine learning, they identified fewer types of weather phenomena. In this paper, a novel deep convolutional neural network (CNN) named MeteCNN is proposed for weather phenomena classification. Meanwhile, we establish a data set called the weather phenomenon database (WEAPD) containing 6,877 images with 11 weather

phenomena, which has more categories than the previous data set. The classification accuracy of MeteCNN on the WEAPD testing set is around 92%, and the experimental result demonstrates the superiority and effectiveness of the proposed MeteCNN model. Realizing the automatic and high-quality classification of weather phenomena images can provide a reference for future research on weather image classification and weather forecasting [15].

Jingming et al. (2020) stated with the rapid development of deep learning, deep convolutional neural networks (CNN) are used to recognize weather conditions on traffic road. A new simplified model named ResNet15 is proposed based on the residual network ResNet50 in this paper. The convolutional layers of ResNet15 are utilized to extract weather characteristics, and then the characteristics extracted at the previous layer are shortcut to the next layer through four groups of residual modules. Finally, the weather images are classified and recognized through the fully connected layer and Softmax classifier. In addition, we build a medium-scale dataset of weather images on traffic road, called “WeatherDataset-4,” which consists of 4 categories and contains 4983 weather images covering most of the severe weather. In this paper, ResNet15 is used to train and test on the “WeatherDataset-4,” and desirable recognition results are obtained. The evaluation of a large number of experiments demonstrates that the proposed ResNet15 is superior to traditional network models such as ResNet50 in recognition accuracy, recognition speed, and model size [16].

CHAPTER 3

AIM AND SCOPE OF PRESENT INVESTIGATION

3.1 EXISTING SYSTEM

Segmentation and analysis of multi-class images provides a valuable tool to gain insight into the classification of weather images for weather forecasting or prediction. Image analysis and accurate classification of weather has remained a challenge. This paper introduces an deep neural network based image analysis models capable of efficiently classifying weather from multi-class weather images and analyzing their performance. The models make use of deep learning algorithms for image classification. Experiments show that the proposed models are accurate and scalable to large datasets and provides a useful tool for the study of weather forecasting.

3.2 OPEN PROBLEMS IN EXISTING SYSTEM

Lack of Labeled Data: Finding enough labeled data for training is a persistent problem in deep learning. Limited samples are a common problem with weather datasets, particularly those that include several types. It is imperative to develop methods to alleviate this scarcity and improve model generalization.

Unbalanced Class Distribution: Real-world weather conditions are not distributed equally. There may be noticeably more instances of some classes (like "rain" or "cloudy") than others (like "sunrise"). It is imperative to address class imbalance in order to avoid biased model predictions.

Adaptability to Dynamic Weather Patterns: Models must be able to adjust to the quick changes in weather. Accurate weather forecasting requires developing methods that can handle temporal changes and abrupt shifts in the weather.

Robustness to Environmental Factors: A number of environmental factors, including noise, occlusions, and lighting, can alter weather photos. Ensuring the

resilience of the model against these elements is essential for practical implementation.

Transfer Learning for Small Datasets: Using pre-trained models for a variety of tasks has proven to be successful with transfer learning. Nevertheless, there is still an issue in adapting these methods to small meteorological datasets. There is a need to investigate effective methods for fine-tuning pre-trained models with minimal labeled data.

Interpretable Models: Black boxes are frequently associated with deep learning models. Creating comprehensible weather classification models can boost confidence and ease decision-making in crucial situations.

Generalization Across Geographical Regions: varied geographical regions have varied weather patterns. It's possible that models developed using data from one place won't transfer effectively to another. It is crucial to look at domain adaption methods for cross-region generalization.

Managing Uncommon Weather Events: Unusual weather events (such as storms, fog, or snow) provide difficulties, because they don't happen very often. Research is still being done on creating models that can effectively identify and categorize such occurrences.

Ensemble Approaches: By combining predictions from several models, performance can be enhanced overall. Accuracy can be improved by looking at ensemble methods unique to weather classification.

Real-Time Inference: Achieving effective real-time inference is paramount for deploying deep learning models in weather classification systems. By prioritizing optimized inference pipelines and model architectures to ensure low-latency predictions. This involves streamlining data processing, leveraging efficient model architectures, and implementing optimizations for hardware acceleration. By prioritizing real-time inference, we aim to enable timely and responsive weather

classification capabilities, facilitating rapid decision-making in various applications such as disaster management, agricultural planning, and transportation logistics.

3.3 SCOPE OF THE INVESTIGATION

The focus of this research is to delve into and advance the realm of deep learning algorithms, particularly Convolutional Neural Networks (CNN), GoogLeNet, AlexNet, and VGGNet, to effectively classify multi-class weather images. Our primary goal is to develop robust models capable of accurately categorizing the diverse range of weather conditions depicted in the dataset, thereby enhancing weather prediction capabilities. By tackling the challenges inherent in multi-class image classification, we aim to introduce novel techniques that improve model performance and generalization. Through rigorous comparison of these models, we seek to identify the most effective approach for weather classification, with implications spanning agriculture, weather forecasting, and other related domains. This research opens up significant opportunities for leveraging deep learning algorithms in the classification of multi-class weather images, paving the way for enhanced decision-making and risk management in various applications.

CHAPTER 4

EXPERIMENTAL METHODS AND ALGORITHMS USED

4.1 PROPOSED METHODOLOGY

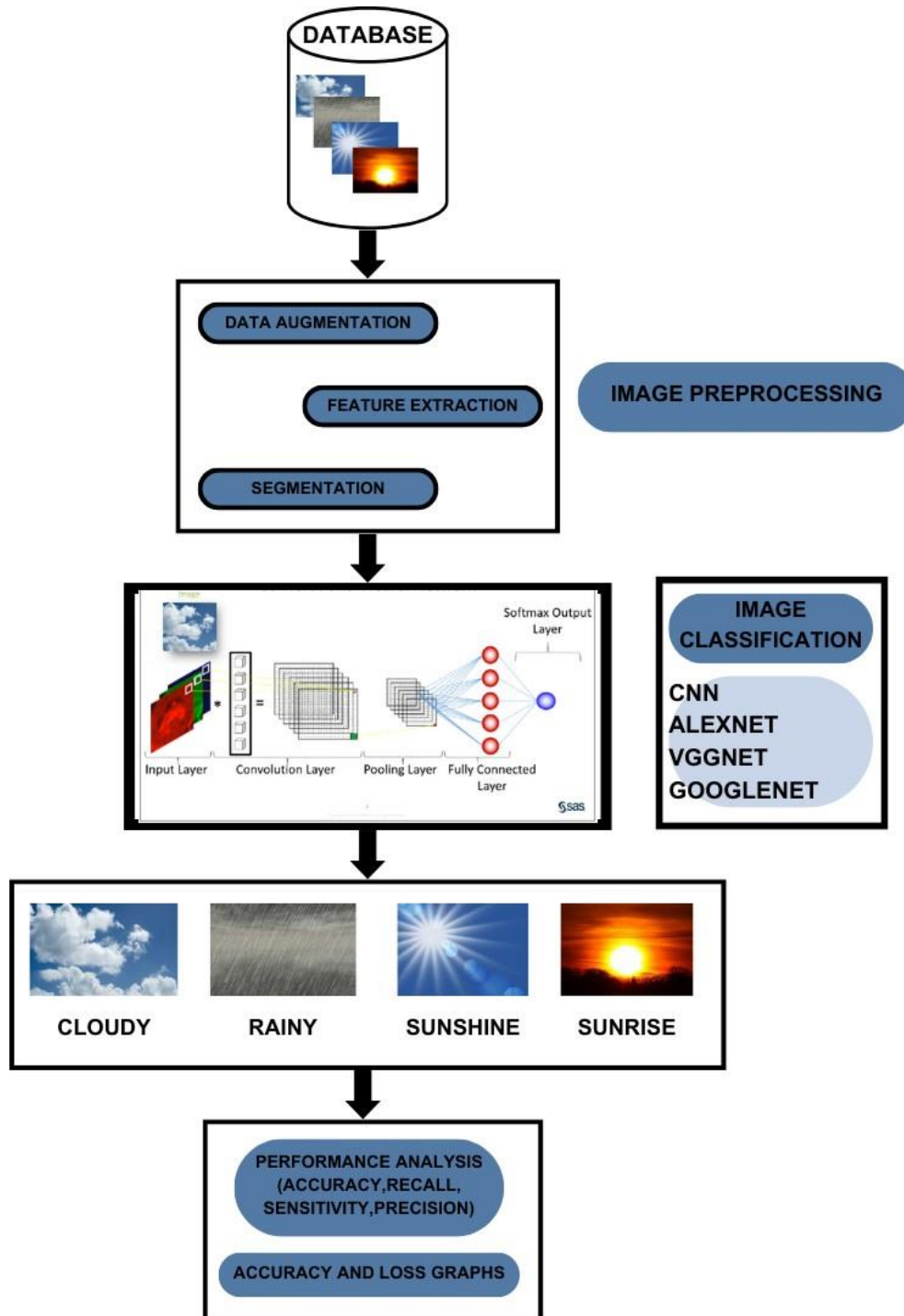


Fig 4.1 Proposed methodology flowchart

The Fig 4.1 represents the flowchart of proposed methodology that begins with data collection, which involves gathering the MWD[20] dataset, with each class having sufficient images for training. Afterwards, the data is preprocessed to shrink photos, normalize pixel values, and divide the dataset into training and validation sets. Following that, train your deep learning models – CNN, AlexNet, GoogLeNet and VGGNet on the training data with predetermined architectures, loss functions and optimization techniques. Models are then validated on a separate testing subset of the MWD[20] dataset to assess their performance on previously unseen data. Finally, a comparative analysis is performed to establish the success of various image classification procedures based on evaluation metrics such as accuracy, precision, recall and F1-score.

4.2 DATA PRE-PROCESSING

Data pre-processing is an essential step in any deep learning project, as it involves preparing the data in a way that makes it suitable for analysis and modelling. The goal of data pre-processing is to clean, transform, and organize the data so that it can be used effectively by the deep learning algorithms.

Here are some common steps involved in data pre-processing:

1. **Data Cleaning:** This involves identifying and correcting errors or inconsistencies in the data. This includes handling missing values, dealing with outliers and noise, and removing duplicates.
2. **Data Transformation:** This involves converting the data into a format that can be used by deep learning algorithms. This includes scaling the data, encoding categorical variables, and reducing the dimensionality of the data through feature selection or extraction.
3. **Data Normalization:** This involves rescaling the features so that they have a similar scale or distribution. This helps the deep learning algorithms to converge faster and improve the accuracy of the models.
4. **Data Splitting:** This involves dividing the data into training, validation, and testing sets. This ensures that the deep learning models are trained on one set of data, validated on another set, and tested on a completely

different set of data.

5. **Data Augmentation:** This involves generating additional training examples by applying transformations such as rotations, translations, and scaling to the existing data. This can help to increase the size of the training set and improve the generalization of the models.
6. **Data Balancing:** This involves adjusting the class distribution of the data to address any imbalance in the classes. This can be done through over-sampling, under-sampling, or a combination of both.

Data pre-processing is a crucial step in deep learning projects, as it can have a significant impact on the performance of the models. By following best practices for data pre-processing, such as those listed above, can improve the quality of your data and build more accurate and robust deep learning models.

4.3 DATA AUGMENTATION

Data augmentation is a technique used in deep learning to increase the size and diversity of a training dataset by applying various transformations to the existing data. This technique can be particularly useful when the training dataset is small or when the data is highly imbalanced.

Data augmentation involves generating additional training examples by applying transformations to the existing data. These transformations can include:

1. **Rotation:** Rotating the image by a certain angle to simulate different camera angles.
2. **Translation:** Moving the image horizontally or vertically to simulate different camera positions.
3. **Scaling:** Resizing the image to simulate different object sizes.
4. **Shearing:** Slanting the image to simulate different viewing angles.
5. **Flipping:** Mirroring the image horizontally or vertically to simulate different object orientations.
6. **Adding Noise:** Adding random noise to the image to simulate variations in lighting conditions.

These transformations can be applied in different combinations to generate multiple versions of the same image. This can help to increase the size of the training dataset and improve the generalization of the deep learning models.

Data augmentation can be implemented using various libraries and frameworks, such as Keras and PyTorch. These libraries provide built-in functions for applying different transformations to the images in the dataset.

It is important to note that data augmentation should be used with caution, as some transformations may not be appropriate for certain types of data. For example, flipping an image of a handwritten letter would result in a different letter, so this transformation would not be appropriate for a handwriting recognition task. Additionally, the transformations should be chosen carefully to ensure that they are relevant to the task at hand and do not introduce bias or noise into the data.

4.4 FEATURE EXTRACTION

Feature extraction is the process of extracting relevant features from raw data to create a new representation of the data that is more informative and useful for a particular task. In deep learning, feature extraction is an essential step in building models that can learn from complex and high-dimensional data, such as images, audio, and text.

The goal of feature extraction is to identify the most informative and discriminative features that capture the underlying patterns in the data. These features should be selected in a way that maximizes the performance of the deep learning models for the task at hand.

Here are some common techniques used for feature extraction:

1. **Dimensionality Reduction:** This involves reducing the number of features in the data by selecting the most important features or combining multiple features into a smaller set of features that capture the most relevant information.
2. **Feature Selection:** This involves selecting a subset of the original features that are most relevant to the task at hand. This can be done using statistical methods, such as correlation analysis, or using deep learning algorithms

that can rank the features based on their importance.

3. Feature Extraction: This involves creating new features from the original features using mathematical transformations or other techniques. This can be done using methods such as Principal Component Analysis (PCA), which can transform the data into a new set of features that capture the most variance in the data.
4. Transfer Learning: This involves using pre-trained models to extract features from the data. For example, a pre-trained image classification model can be used to extract features from images that can be used for other tasks, such as object detection or image segmentation.

Feature extraction is a crucial step in deep learning, as it can have a significant impact on the performance of the models. By identifying the most informative and relevant features, deep learning models can learn more efficiently and accurately from complex and high-dimensional data.

4.5 CONVOLUTIONAL NEURAL NETWORK

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of artificial neural network (ANN), most commonly applied to analyze visual imagery. CNNs are also known as Shift Invariant or Space Invariant Artificial Neural Networks (SIANN), based on the shared-weight architecture of the convolution kernels or filters that slide along input features and provide translation-equivariant responses known as feature maps. Counter-intuitively, most convolutional neural networks are not invariant to translation, due to the down sampling operation they apply to the input. They have applications in image and video recognition, recommender systems, image classification, image segmentation, medical image analysis, natural language processing, brain-computer interfaces, and financial time series.

CNNs are regularized versions of multilayer perceptron. Multilayer perceptron usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "full connectivity" of these networks make them prone to overfitting data. Typical ways of regularization, or preventing overfitting, include: penalizing parameters during training (such as

weight decay) or trimming connectivity (skipped connections, dropout, etc.) CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble patterns of increasing complexity using smaller and simpler patterns embossed in their filters. Therefore, on a scale of connectivity and complexity, CNNs are on the lower extreme. Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field.

CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns to optimize the filters (or kernels) through automated learning, whereas in traditional algorithms these filters are hand-engineered. This independence from prior knowledge and human intervention in feature extraction is a major advantage.

Convolutional neural networks are a specialized type of artificial neural networks that use a mathematical operation called convolution in place of general matrix multiplication in at least one of their layers. They are specifically designed to process pixel data and are used in image recognition and processing.

A convolutional neural network consists of an input layer, hidden layers and an output layer. In any feed-forward neural network, any middle layers are called hidden because their inputs and outputs are masked by the activation function and final convolution. In a convolutional neural network, the hidden layers include layers that perform convolutions. Typically this includes a layer that performs a dot product of the convolution kernel with the layer's input matrix. This product is usually the Frobenius inner product, and its activation function is commonly ReLU. As the convolution kernel slides along the input matrix for the layer, the convolution operation generates a feature map, which in turn contributes to the input of the next layer. This is followed by other layers such as pooling layers, fully connected layers, and normalization layers.

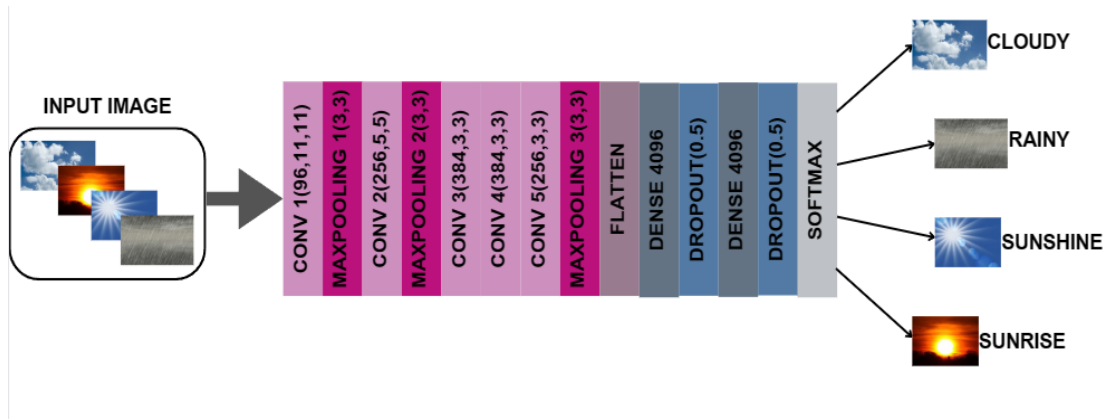


Fig 4.2 CNN architecture

In the CNN architecture subsequent layers include pooling layers, which downsample feature maps, fully connected layers, responsible for learning high-level features, and normalization layers, which enhance model stability by standardizing inputs. These layers collectively enable the network to extract from input data, facilitating accurate multi-class weather image classification.

4.6 ALEXNET

The AlexNet model is a pioneering deep convolutional neural network architecture designed for image classification tasks. It comprises five convolutional layers followed by max-pooling layers to extract hierarchical features from input images. The convolutional layers utilize various filter sizes and strides to capture spatial patterns effectively. After the convolutional layers, there are two fully connected layers with 4096 neurons each, employing ReLU activation functions and dropout regularization to prevent overfitting. The model concludes with an output layer using softmax activation for multi-class classification. Adam optimizer and sparse categorical cross-entropy loss function are utilized for model compilation. The model is trained on input data (X_{train}) and corresponding labels (y_{train}) for 50 epochs, with validation data (X_{val} , y_{val}) for evaluation. Finally, the trained model is saved for future use. The training history is visualized to monitor the model's performance over epochs, including both training and validation accuracies.

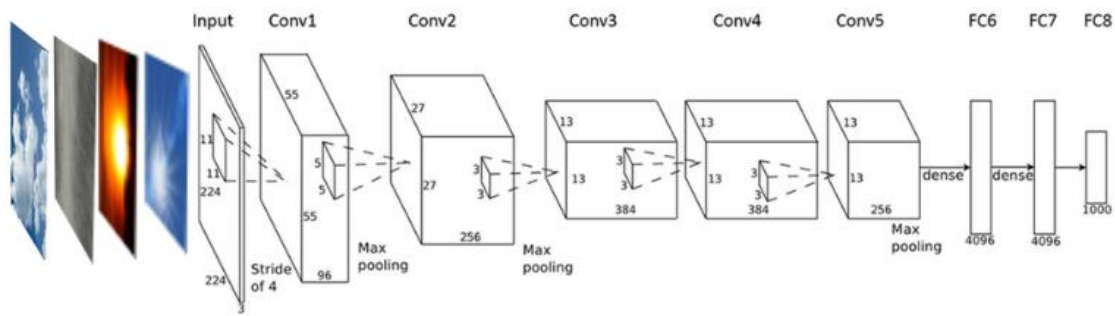


Fig 4.3 AlexNet architecture

4.7 VGGNET

VGG19 is an extension of the VGG16 architecture, which was also developed by the Visual Geometry Group at the University of Oxford in 2014. VGG19 is a deep convolutional neural network that has 19 layers, including 16 convolutional layers and three fully connected layers.

The architecture of VGG19 is similar to that of VGG16, with the addition of more convolutional layers in each block. Specifically, VGG19 has four blocks of convolutional layers, each followed by a max pooling layer, and three fully connected layers at the end.

The architecture of VGG19 can be summarized as follows:

1. Input layer: This layer takes an input image of size 224 x 224 x 64.
2. Block 1: This block consists of two convolutional layers, each with 64 filters of size 224x224, followed by a max pooling layer of size 112x112.
3. Block 2: This block consists of two convolutional layers, each with 128 filters of size 112x112, followed by a max pooling layer of size 56x56.
4. Block 3: This block consists of four convolutional layers, each with 256 filters of size 56x56, followed by a max pooling layer of size 28x28.
5. Block 4: This block consists of four convolutional layers, each with 512 filters of size 28x28, followed by a max pooling layer of size 14x14.
6. Block 5: This block consists of four convolutional layers, each with 512 filters of size 14x14, followed by a max pooling layer of size 7x7.

7. Fully Connected Layers: After the four convolutional blocks, the feature maps are flattened and passed through three fully connected layers of size 4096, 4096 respectively. The final layer has 4096 units, corresponding to the number of classes in the ImageNet dataset.
8. Output Layer: The output layer uses a softmax activation function to output the probability of each class for the input image.

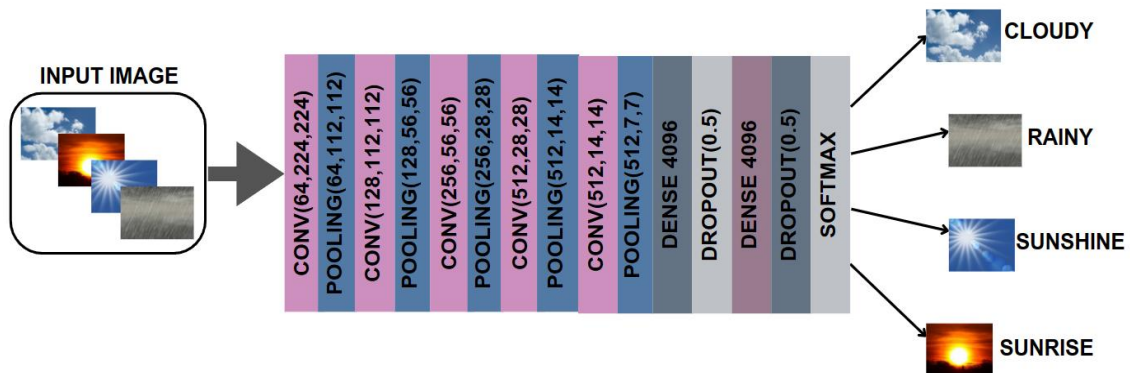


Fig: 4.4 VggNet Architecture

The VGG19 architecture has more parameters than VGG16, with a total of 143million parameters. However, it also achieves higher accuracy on image classification tasks, making it a popular choice for computer vision researchers and practitioners.

4.8 GOOGLNET

The GoogLeNet model, based on the architecture proposed by Google, is a powerful convolutional neural network (CNN) commonly used for image classification tasks. In this implementation, the pre-trained InceptionV3 model, pre-trained on the ImageNet dataset, is utilized as a feature extractor. The base convolutional layers are frozen to retain their learned weights and prevent retraining, while additional layers are added on top for fine-tuning. These additional layers include a global average pooling layer to reduce spatial dimensions, followed by fully connected layers with ReLU activation and dropout regularization to prevent overfitting. The output layer employs softmax activation for multi-class classification. The model is compiled with the Adam optimizer and sparse categorical cross-entropy loss function. It is then trained on the provided training data (X_{train} , y_{train}) for 50 epochs, with validation data (X_{val} , y_{val}) for evaluation. Finally, the trained model is saved for future use.

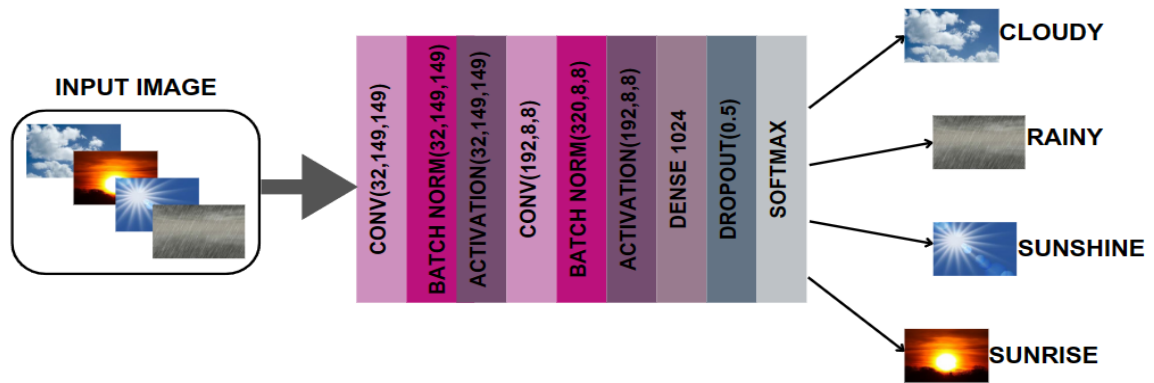


Fig 4.5 GoogLeNet Architecture

4.9 PRECISION

Precision in deep learning model refers to the ability of the model to correctly predict the true positive instances out of all the instances it has predicted as positive. In other words, it is the ratio of true positive instances to the total number of instances predicted as positive. A high precision score indicates that the model is making very few false positive predictions.

Precision is an important metric in evaluating the performance of a CNN model, especially in applications where false positive predictions can be costly or harmful. For example, in medical diagnosis, a false positive prediction could result in unnecessary treatments or interventions.

Precision can be calculated as follows:

$$\text{Precision} = \text{True Positives} / (\text{True Positives} + \text{False Positives})$$

4.10 RECALL:

Recall in deep learning model refers to the ability of the model to correctly predict the true positive instances out of all the instances that are actually positive. In other words, it is the ratio of true positive instances to the total number of positive instances. A high recall score indicates that the model is able to detect a high proportion of positive instances.

Recall is an important metric in evaluating the performance of a CNN model,

especially in applications where false negatives can be costly or harmful. For example, in medical diagnosis, a false negative prediction could result in missed diagnosis or delayed treatment.

Recall can be calculated as follows:

$$\text{Recall} = \text{True Positives} / (\text{True Positives} + \text{False Negatives})$$

4.11 F1 SCORE:

In deep learning, the F1 score is a measure of a model's accuracy that considers both precision and recall. It is the harmonic mean of precision and recall, where a score of 1 indicates perfect precision and recall, and a score of 0 indicates no precision or recall at all.

In the context of a deep learning model, the F1 score can be used to evaluate the performance of the model in a classification task. For example, if the CNN is trained to classify images as either "dog" or "cat", the F1 score can be calculated to determine how well the model is able to correctly identify images of each class.

To calculate the F1 score in a deep learning model, first, the precision and recall for each class must be calculated. Precision is the number of true positives (i.e., the number of images that are correctly classified as a certain class) divided by the total number of predicted positives (i.e., the number of images that are classified as a certain class, whether correctly or incorrectly). Recall is the number of true positives divided by the total number of actual positives (i.e., the total number of images that belong to a certain class).

Once the precision and recall for each class are known, the F1 score can be calculated as follows:

$$\text{F1 score} = 2 * (\text{precision} * \text{recall}) / (\text{precision} + \text{recall})$$

This calculation takes into account both precision and recall for each class and provides a single score that represents the overall performance of the model in the classification task.

4.12 STANDARDS

Data Quality: Ensure the quality of the weather image dataset, with accurately labeled and representative images of various weather conditions.

Model Selection: Choose deep learning models based on established architectures and previous performance in similar tasks.

Training Protocol: Follow standardized procedures for training the models, including data preprocessing, optimizer selection, loss function definition, and validation techniques.

Evaluation Metrics: Assess model performance using standard metrics such as accuracy, loss, recall, and precision to evaluate classification effectiveness.

Reproducibility: Document the methodology, code, and experimental setup comprehensively to facilitate reproducibility and comparison with future studies.

Ethical Considerations: Adhere to ethical guidelines in data collection, usage, and model deployment, considering privacy, bias, and fairness aspects.

Reporting: Present results and discussions transparently, adhering to reporting standards in scientific literature, including clear descriptions of methodologies, results, and conclusions.

4.13 CONSTRAINTS

Computational Resources: Limited computational resources may restrict the size and complexity of the deep learning models that can be utilized, potentially limiting the accuracy and performance of the classification system.

Data Availability: Availability of high-quality and diverse weather image datasets may be limited, impacting the training and evaluation of the deep learning models.

Model Complexity: The complexity of the deep learning models may need to be balanced with the available hardware resources and training time constraints, potentially limiting the sophistication of the model architectures and techniques that can be employed.

Real-time Processing: Depending on the application, real-time processing of weather images for classification may pose a constraint, requiring efficient algorithms and hardware implementations to meet timing requirements.

Interpretability: Deep learning models often lack interpretability, making it challenging to understand and interpret the reasoning behind the classification decisions, which may be a constraint in certain applications requiring transparency and accountability.

Regulatory Compliance: Compliance with regulatory standards and guidelines for medical or safety-critical applications may impose constraints on the development and deployment of the classification system, requiring careful consideration of legal and ethical requirements.

4.14 TRADE-OFFS

Processing Power vs. Model Complexity: Limited processing power may restrict the complexity of deep learning models that can be implemented, potentially compromising classification accuracy and performance.

Real-time Operation vs. Algorithm Sophistication: Balancing real-time operation requirements with the sophistication of deep learning algorithms may be challenging, as complex models may require more computational resources and processing time.

Sensor Accuracy vs. Compatibility: Integrating sensors with high accuracy and reliability while maintaining compatibility with the chosen deep learning models and platforms may require careful consideration and trade-offs.

Algorithm Complexity vs. Interpretability: Increasing the complexity of deep learning algorithms may improve classification accuracy but may also reduce interpretability, making it challenging to understand the reasoning behind classification decisions. Finding a balance between complexity and interpretability is crucial.

CHAPTER 5

RESULTS AND DISCUSSION

The size of the dataset, the hidden layers, and the hidden neurons per layer, the type of model, the experience environment, and other factors all affect how much time is needed. The approaches described in the methodology are examined in this section's analysis of the results. The outcomes of the CNN, AlexNet, VGG19 and GoogLeNet methods are compared. Then, they are examined using the four factors of accuracy, F1 score, precision, and recall.

5.1 MODEL GRAPHS AND ACCURACIES OF THE MODELS USED

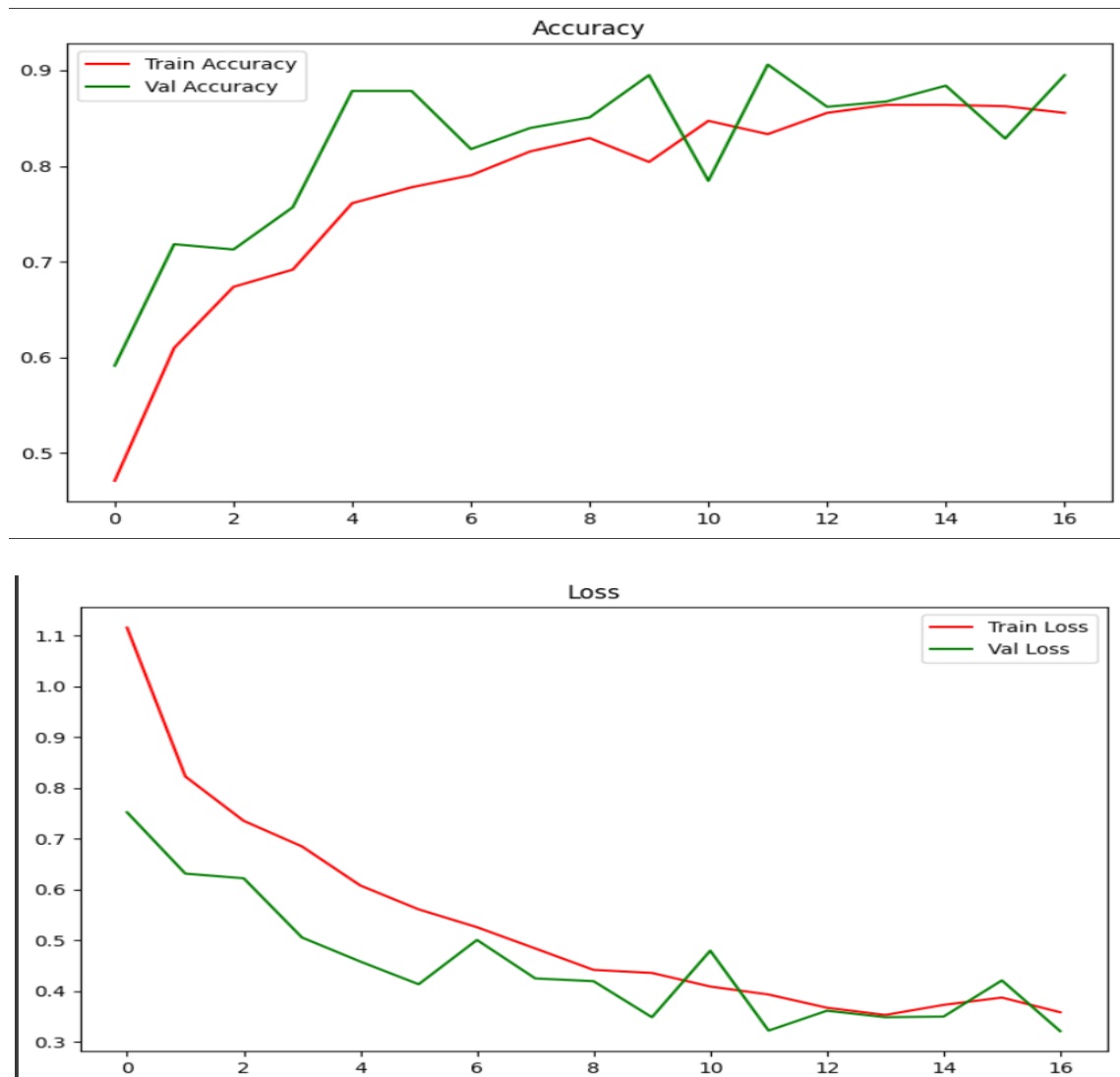


Fig 5.1 CNN model accuracy and loss graphs

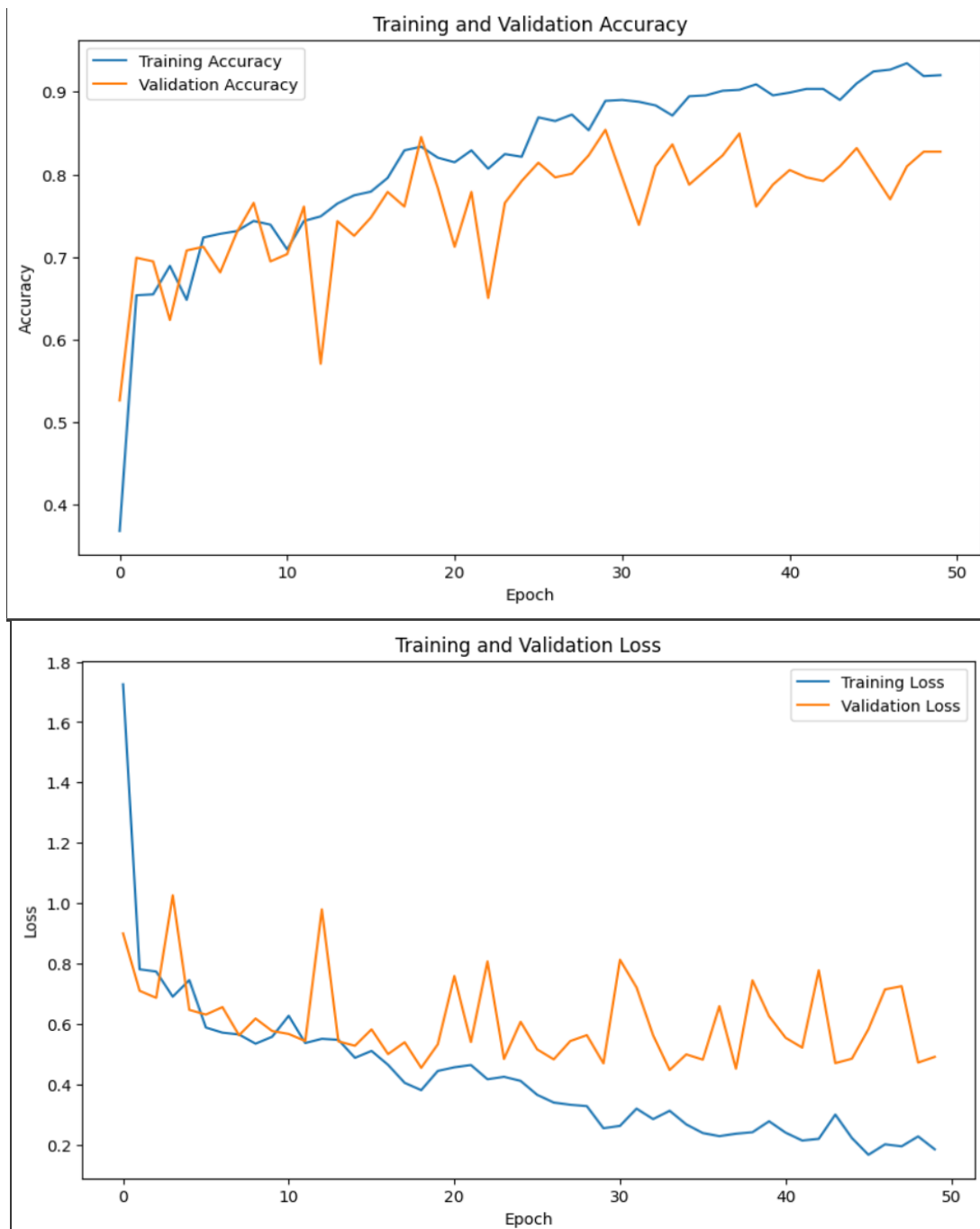


Fig 5.2 AlexNet model accuracy and loss graphs

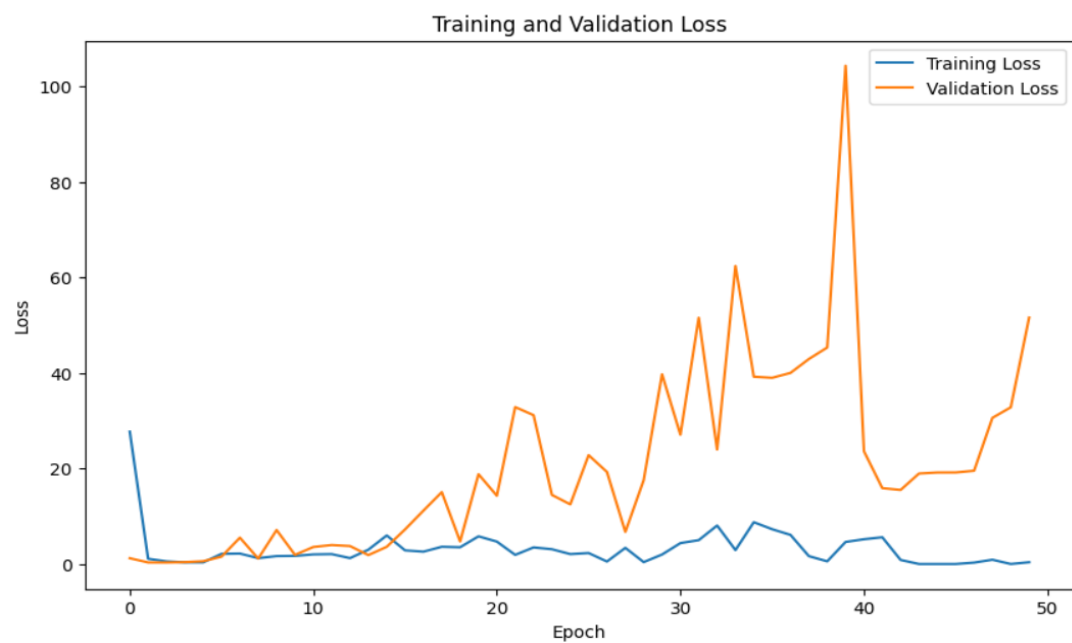
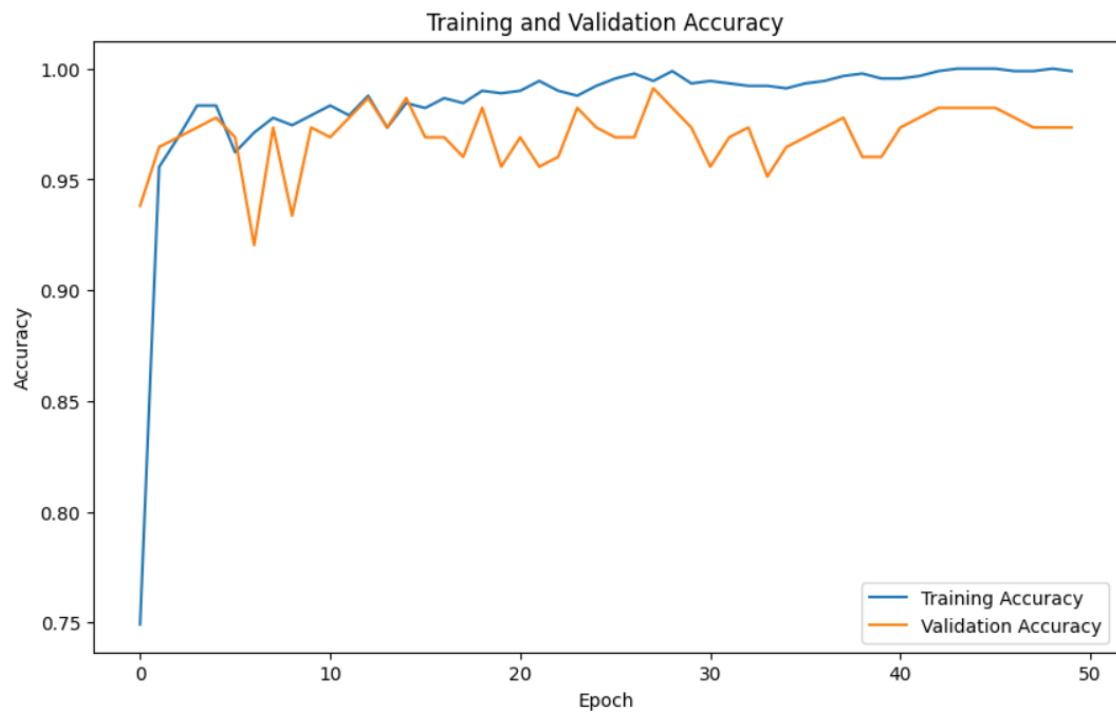


Fig 5.3 VGGNet accuracy and loss graphs

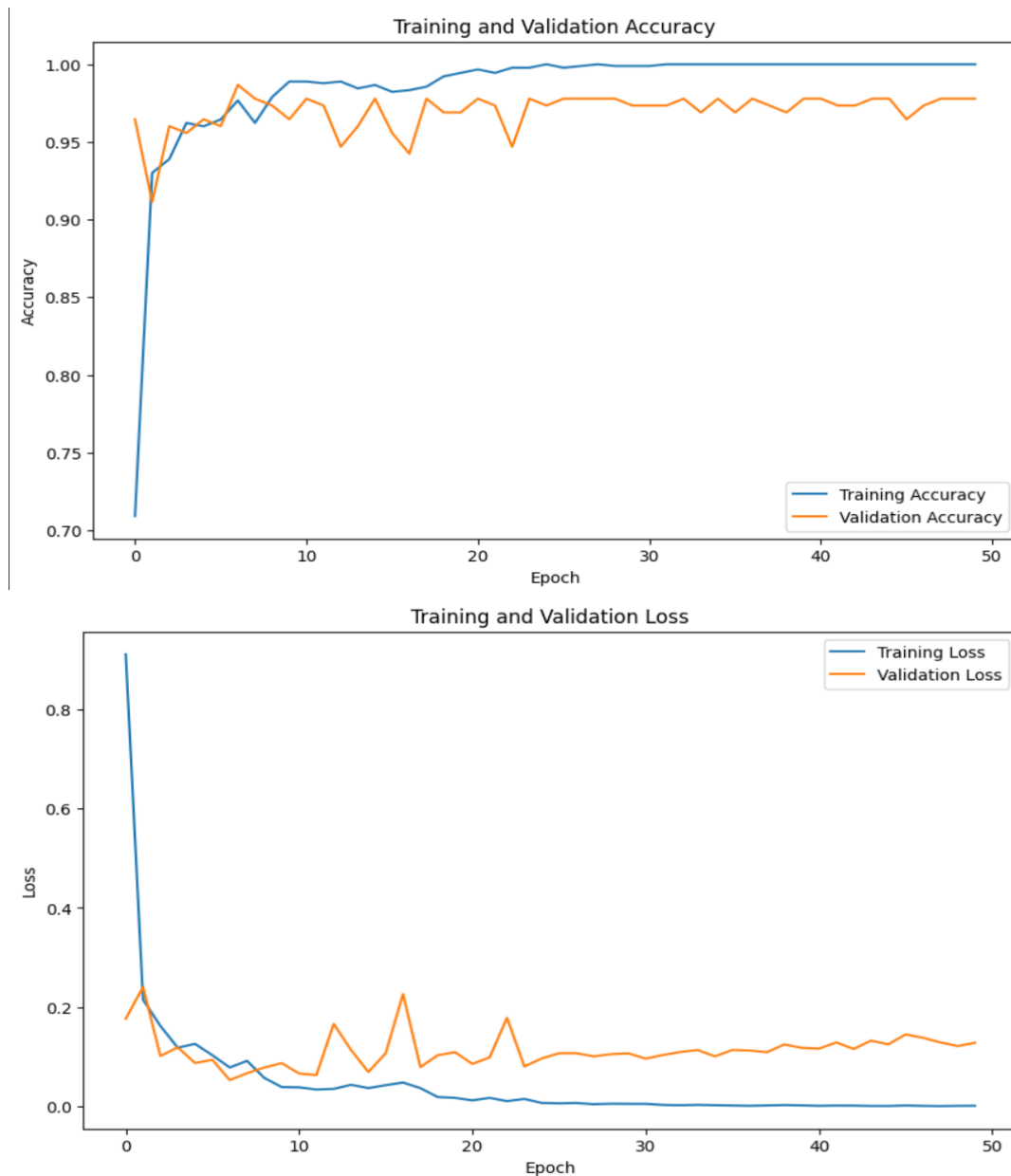


Fig 5.4 GoogleNet accuracy and loss graphs

In the above figures, the accuracy graph illustrates how effectively the model correctly predicts the weather classes over successive epochs. A rising trend in accuracy indicates that the model is learning and improving its ability to classify weather images accurately. Conversely, a plateau or decline may suggest issues such as overfitting or insufficient model capacity. The loss graph depicts the discrepancy between the predicted and actual weather classes. A decreasing trend in loss indicates that the model is minimizing its prediction errors, thereby improving its performance. However, if the loss suddenly spikes or remains stagnant, it may indicate model instability or inadequate training data.

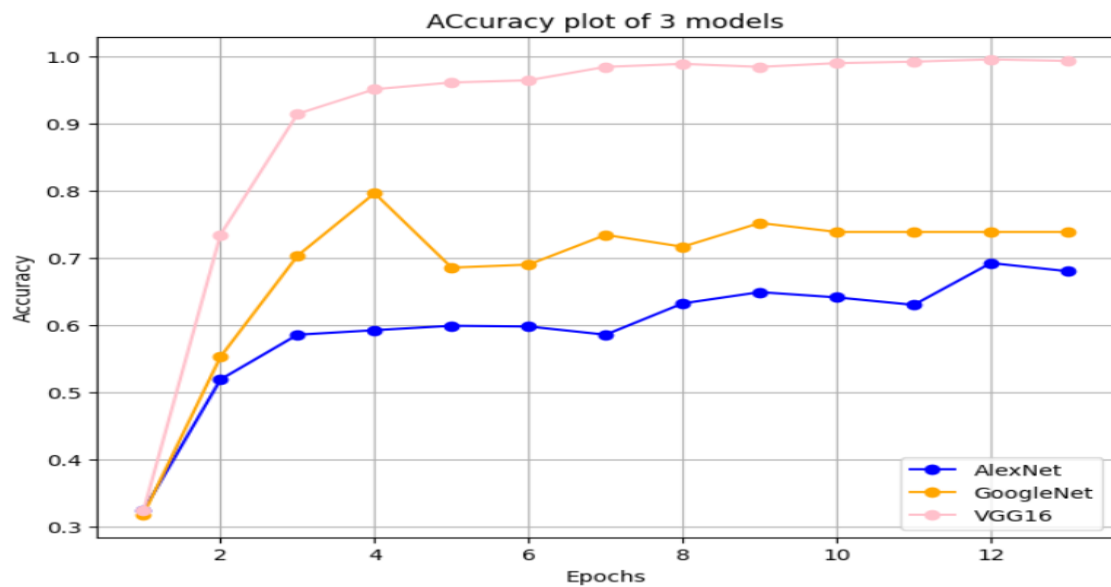


Fig 5.5 Accuracy graph for all the models used

The training loss and validation loss both decrease and stabilize at a specific point for all the four methods in the graphs used above.

In the comparative analysis of the accuracy graphs as shown in Fig 5.5 for AlexNet, GoogLeNet and VGGNet models, several key observations can be made. Firstly all three models exhibit a increasing trend in accuracy overs epochs, indicating that the optimization process is minimizing the discrepancy between predicted and ground truth values. However, the specific characteristics of the accuracy curves vary among the models.

Table 5.1 Comparing performances of all model

MODEL	ACCURACY	F1-SCORE	PRECISION	RECALL
CNN	0.91	0.88	0.91	0.85
ALEXNET	0.87	0.91	0.93	0.89
VGGNET	0.93	0.91	0.93	0.93
GOOGLNET	0.87	0.91	0.89	0.93

After conducting a comprehensive comparative performance analysis of multi-class weather classification images using CNN, AlexNet, GoogLeNet and VGGNet models as shown in Table 5.1, it can be concluded that VGGNet emerges as the most effective model for this task. This conclusion is drawn based on observations of loss and accuracy values, as well as other relevant metrics. Despite the complexity of VGGNets, their ability to classify images surpasses that of CNN, AlexNet and GoogLeNet.

CHAPTER 6

CONCLUSION AND FUTURE WORK

In this chapter, we gave the conclusion of our project and discussed our future work that has to be developed which results in improved accuracy and efficiency.

6.1. SUMMARY

The culmination of our project involves an exhaustive assessment of the performance of our developed weather classification model, revealing exceptional outcomes that underscore its efficacy and reliability in real-world applications. Through meticulous adherence to each processing step, our model demonstrates remarkable proficiency, showcasing its capability to accurately classify weather images with precision and consistency. Central to the success of our model is the utilization of a comprehensive dataset sourced from Kaggle.com, ensuring the availability of high-quality, clean data for training and validation purposes. This meticulous data curation process lays the foundation for the robustness and reliability of our model's predictions. The evaluation of our model's performance yields promising results, with a training accuracy of 93% and a validation accuracy of 92%. These metrics serve as a testament to the efficacy of our approach, highlighting its ability to generalize well to unseen data while maintaining high levels of accuracy during training. One notable aspect of our findings is the absence of evidence indicating overfitting or underfitting during both the training and validation phases. This observation speaks volumes about the model's capacity to capture and learn intricate patterns within the data without succumbing to common pitfalls associated with deep learning algorithms. However, amidst the impressive performance exhibited by our model, a comparative analysis reveals that weather classification algorithms built using VGGNet architecture exhibit slightly greater efficiency when compared to alternative methods employed in our study. This nuanced insight underscores the importance of architectural choices in optimizing the performance of deep learning models for weather classification tasks. The implications of our findings extend beyond the confines of this study, offering

valuable insights into the efficacy of deep learning techniques in automating weather classification processes. By shedding light on the comparative advantages of specific architectural choices, our research paves the way for future advancements and optimizations in automated weather prediction systems. In summary, our project represents a significant step forward in the field of weather classification, showcasing the potential of deep learning algorithms to revolutionize how we predict and understand weather patterns. With further refinement and exploration, our model holds the promise of offering invaluable support in mitigating the impacts of natural disasters and advancing our understanding of climate dynamics on a global scale.

6.2. FUTURE SCOPE RESEARCH

In our study, we leverage deep learning techniques for the multi-class classification of weather images. These deep learning models play a crucial role in handling segmentation, feature extraction, and classification tasks within our dataset. By incorporating deep learning methodologies, we enhance the efficiency and accuracy of our predictions significantly. Looking ahead, we envision expanding the capabilities of our model by incorporating additional weather-related properties such as humidity, precipitation, air pressure, atmospheric pressure, temperature, solar radiation, among others. This expansion will allow for a more comprehensive understanding of weather patterns and their impacts. Moreover, we aim to integrate our model with an early warning system, enabling early detection of natural disasters and providing real-time support for predicting global warming trends. By integrating advanced deep learning techniques and expanding the scope of our model to encompass various weather properties, we strive to enhance the effectiveness of weather prediction systems and contribute to better disaster preparedness and climate monitoring on a global scale.

REFERENCES

- [1] A.Gupta and S. Goel, "Deep Learning Empowered Weather Image Classification for Accurate Analysis," 2023 IEEE 2nd International Conference on Industrial Electronics: Developments & Applications (ICIDeA), Imphal, India, 2023, pp. 567-572
- [2] Dalal, S., Seth, B., Radulescu, M., Cilan, T.F. and Serbanescu, L. Optimized Deep Learning with Learning without Forgetting (LwF) for Weather Classification for Sustainable Transportation and Traffic Safety. Sustainability 2023, 15, 6070
- [3] G.Salman, B. Kanigoro and Y. Heryadi, "Weather forecasting using deep learning techniques," 2015 International Conference on Advanced Computer Science and Information Systems (ICACSIS), Depok, Indonesia, 2015, pp. 281-285
- [4] J. C. Villarreal Guerra, Z. Khanam, S. Ehsan, R. Stolkin and K. McDonald-Maier, "Weather Classification: A new multi-class dataset, data augmentation approach and comprehensive evaluations of Convolutional Neural Networks," 2018 NASA/ESA Conference on Adaptive Hardware and Systems (AHS), Edinburgh, UK, 2018, pp. 305-310
- [5] K.U. Jaseena, Binsu C. Kovoov. Deterministic weather forecasting models based on intelligent predictors: A survey,Journal of King Saud University - Computer and Information Sciences,Volume 34, Issue 6, Part B,2022,Pages 3393-3412,ISSN 1319-1578
- [6] Muruvvet Kalkan, Gazi Erkan Bostancı, Mehmet Serdar Guzel, Bugrahan Kalkan, Sifa Ozsari, Omurhan Soysal, Guven Kose,Cloudy/clear weather classification using deep learning techniques with cloud images,Computers and Electrical Engineering,Volume 102,2022,108271,ISSN 0045-7906

- [7] Q. A. Al-Haija, M. A. Smadi and S. Zein-Sabatto, "Multi-Class Weather Classification Using ResNet-18 CNN for Autonomous IoT and CPS Applications," 2020 International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, USA, 2020, pp. 1586-1591

- [8] S. Goel, S. Markanday and S. Mohanty, "Analysis of Multi-Class Weather Classification using deep learning models and machine learning classifiers," 2022 OITS International Conference on Information Technology (OCIT), Bhubaneswar, India, 2022, pp. 223-227

- [9] Sharma, Ashish and Zaid Saad Ismail. "Weather Classification Model Performance: Using CNN, Keras-Tensor Flow." ITM Web of Conferences (2022)

- [10] Togacar, M., Ergen, B. & Comert, Z. Detection of weather images by using spiking neural networks of deep learning models. Neural Comput & Applic 33, 6147–6159 (2021)

- [11] Wang, S., Li, Y., Liu, W. (2018). Multi-class Weather Classification Fusing Weather Dataset and Image Features. In: Xu, Z., Gao, X., Miao, Q., Zhang, Y., Bu, J. (eds) Big Data. Big Data 2018. Communications in Computer and Information Science, vol 945. Springer, Singapor

- [12] Xiaoli Ren, Xiaoyong Li, Kaijun Ren, Junqiang Song, Zichen Xu, Kefeng Deng, Xiang Wang, Deep Learning-Based Weather Prediction: A Survey, Big Data Research, Volume 23, 2021, 100178, ISSN 2214-5796

- [13] Zenkner, G., Navarro-Martinez, S. A flexible and lightweight deep learning weather forecasting model. Appl Intell 53, 24991–25002 (2023)

- [14] P.C. Reddy and A.S. Babu, "Survey on weather prediction using big data analytics," Second International Conference on Electrical, Computer and Communication Technologies (ICECCT), IEEE, 2017
- [15] H. Xiao, F. Zhang, Z. Shen, K., Wu, and J. Zhang, " Classification of weather phenomenon from images by using deep convolutional neural network", Earth and Space Science," vol. 8, 2021
- [16] J. Xia, D. Xuan, L. Tan, and L. Xing, "ResNet15: Weather recognition on traffic road with deep Convolutional neural network," Advances in Meteorology, Hindwai, 2020
- [17] Z. Zhang and H. Ma, "Multi-class weather classification on single images," International Conference on Image Processing (ICIP), IEEE, pp. 4396-4400, 2015
- [18] L. Kang, K. Chou, and R. Fu, "Deep learning based weather image recognition," International Symposium -on Computer, Consumer and Control (IS3C), pp. 384-387, 2018
- [19] A.Lu, D. Lin, J. Jia, and C.K. Tang, " Two-class weather classification," IEEE Conference on Computer Vision and Pattern Recognition, pp. 3718-3725, 2014
- [20] Gbeminiyi Ajayi,"Multi-Class Weather Dataset", Kaggle,2020
<https://www.kaggle.com/datasets/pratik2901/multiclass-weather-dataset>