A deep learning approach for automatic traffic surveillance under extreme climatic conditions

MSc Research Project
Master of Science in Data Analytics

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A deep learning approach for automatic traffic surveillance under extreme climatic conditions

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Abstract

Machine learning for traffic surveillance has proven to be highly useful in the recent times. In this research two ML (machine learning) models have been developed with VGG16-Net and tested on a secondary dataset. One model predicts the weather conditions prevailing when vehicles travel on the road and the other model predicts accidents caused by certain weather conditions on the road. Two types of weather conditions namely rainy and snowy are being predicted. SGD optimizer and Adam optimization algorithms have been used to optimize the model The loss function used is cross entropy loss. Evaluation of performance is done through accuracy, precision, f1-score and recall parameters. The findings show that the accident prediction model rendered 90% accuracy and the weather prediction model rendered 92% accuracy.

Keywords: Traffic accident, weather prediction, snowy, rainy, VGG16 Net, convolutional neural networks, CNN.

1. Introduction

Automated traffic surveillance in outdoor environments involves both monitoring of objects and actions. Systems for visual surveillance are based on various approaches and include different benefits, i.e. from traffic management to human body tracking. In visual surveillance, one of the major challenges is to describe the features of the object to be detected and to build a model that extracts those features from a captured image dataset. In automatic traffic surveillance, many parameters have been investigated so far. Local weather is an important factor in affecting the traffic (Lagorio et al. 2008). It is critical to provide drivers with access to real-time weather information in order to ensure safe driving in poor weather. As a result of expensive weather stations and frequent manual identification and verification, identifying road weather and conditions can be difficult.

Driver behavior, including lane-keeping, gap maintenance between vehicles, and speed changing behavior, can be greatly impacted by bad weather. Given the detrimental effects of bad weather on drivers' performance, it is crucial to detect and offer road users with actual weather and road conditions, and also the relevant mitigation strategies, via various apps. In this context, deep learning positively contributes to deliver high levels of accuracy, even for challenging image categorization issues. To monitor traffic and keep an eye on the roads, numerous locations have used CCTV cameras for surveillance. Though it is not their primary function, several research (Sirirattanapol, et al 2019) have utilized the video feeds from these cameras to create weather detection systems. When using CCTV images as inputs, Lee et al. (2018) created a model to measure actual meteorological data and discovered an accuracy of more than 80% in measuring the quantity of rainfall. The study by (Khan and Ahmed 2022) demonstrated how pre-trained CNN algorithms could identify surface and weather conditions from video feeds of roadside cameras.

Video cameras were often only used for passive monitoring jobs or extremely simple automated processing in traffic surveillance (Buch, et al 2011; Kanhere and Birchfield 2010). More complex computer vision-based systems are now possible thanks to the improvements made in image processing techniques recently, particularly in the field of deep neural networks. With today's technological advancements, it is possible to design systems that can not only detect automobiles in everyday scenarios but also identify and categories them in conditions that are quite difficult. This might serve as the foundation for carrying out high-level duties like automated traffic management, action detection, new law enforcement, etc (Fernandez, et al 2021). To train the algorithms, the new traffic image collection included real-time traffic images captured in bad weather or under poor lighting conditions, as well as low-resolution images (Fernandez, et al 2021). Deep learning is one of the models that has been playing an important role in object recognition and classification (Sensa, et al 2018). Convolutional neural network (CNN) is a feed-forward machine learning technique with excellent performance and resilience in image recognition. TrafficSensor using deep learning proposed by (Fernandez, et al 2021) has proven to be effective in automatic surveillance despite adverse weather conditions, low resolution and smudged traffic images.

1.2 Problem statement

The number of automobiles on the streets is increasing to a large extent. The rise in the number of moving vehicles creates a different problem for infrastructure management, the economy, and as well the environment. It is obvious that handling such a vast number of automobiles is one of the main issues that countries across the world face. With the world moving more towards automation system, most traffic management system prefer to deploy automated detection systems that can alleviate human operators' workloads as well as ensure accurate and timely detection. Due to the extreme climatic conditions, traditional algorithms frequently aren't able to capture complex patterns in an extreme climate. Thus, the study evaluated and implemented deep learning models based on a huge collection of annotated traffic images. As a result, the proposed system will be capable of performing vehicle counts, identifying traffic irregularities during bad weather, and most crucially, also can scale to numerous traffic cameras.

1.3 Aims and objectives

i. This research aims to develop a deep learning model in order to facilitate the automatic surveillance of traffic during extreme weather conditions and also train and test the model with the help of a secondary dataset.

1.4 Research Questions

i. How can deep learning be applied in facilitating automatic surveillance of traffic during extreme weather conditions like snowfall and rainfall?

1.5 Significance of the study

In addition to monitoring traffic and accessing climatic conditions, automated traffic surveillance systems will also optimize traffic management using machine learning. A rapid development in machine learning and high-performance computing has greatly expanded the application spectrum of video-based traffic monitoring systems. In this work, a system for automatically monitoring traffic is suggested that uses a number of cutting-edge deep learning algorithms depending on the type of traffic operation. Data from annotated video surveillance is used to train deep learning models, and real-time video recordings of moving vehicles in extreme weather conditions are used to evaluate the models. The study emphasizes the importance of intelligent traffic monitoring systems that are vital for reducing congestion and human factors despite climatic conditions. The findings of the current study could be efficiently incorporated into traffic systems including smart traffic surveillance system, smart work zone management, and so on.

1.6 Limitations

i. The study considered only two variables for automatic traffic surveillance in poor weather conditions, i.e. rainfall and snowfall.

ii. The study is also limited to poor climatic conditions alone and does not include other challenges involved in traffic management system, i.e. traffic congestion, work-zone system, etc.

2. Related work

A nation's economic expansion is sometimes gauged by the sharp rise in automobile ownership. However, this expansion also contributes to the issue of terrible traffic congestion. It is crucial to have effective traffic management systems that reduce travel time and costs in order to meet the demands of quick movement for goods, machines, and labor. Since the resources available for the infrastructure are constrained, efficient traffic management is essential for lowering wait times, fuel consumption, and total costs. Although the present traffic management systems can control traffic to some extent, they frequently contain flaws that cause mishaps and traffic congestion. The number of cars and vehicles is fast expanding along with the population in urban areas, which is causing traffic to get more congested and to jam up more frequently (Rashinkar et al, 2018). A traffic monitoring system must be put in place in order to prioritize road safety. In order to overcome these issues and enhance traffic management systems, this chapter will discuss the current deep learning approaches used in automatic traffic surveillance.

2.1. Role of Neural Networks in automatic traffic surveillance:

Convolutional neural networks (CNNs) and other modules, such as graph convolutional networks (GCNs), time convolutional networks (TCNs), recurrent neural networks (RNNs), and support vector regression (SVR) networks, have been used in studies by Yao et al. (2022) and Kashyap et al. (2021) to accurately detect and track vehicles. Compared to conventional neural network models, these models showed better precision and accuracy. In traffic surveillance systems, the classification of vehicles has also been done using neural networks. CNNs have performed remarkably well at categorizing different types of vehicles based on their features and characteristics. For traffic monitoring and congestion management, Boukerche and Wang (2020) compared various neural network models, including RNNs, CNNs, and fast-forward neural networks (FFNNs).

2.2. Deep Learning Techniques for Traffic Surveillance:

Automatic traffic monitoring is essential for controlling traffic, enhancing road safety, and easing congestion. Particularly in challenging traffic situations and inclement weather, traditional surveillance systems sometimes struggle to reliably detect and track vehicles. The effectiveness and efficiency of automatic traffic monitoring systems, however, have shown considerable potential due to recent developments in deep learning techniques. (Jain et al, 2012)

In their study, Kurniawan et al. (2018) proposed a method for detecting intelligent traffic congestion using CCTV camera picture feeds and image classification with convolutional neural networks (CNN). Their approach achieved an average accuracy of 89.50% using a dataset of 1000 CCTV surveillance image feeds.

Fernandez et al. (2021) developed a system consisting of vehicle detection, classification, and tracking modules. They utilized YOLOv3 and YOLOv4-based networks for vehicle detection and a combination of spatial association and KLT tracker for tracking. Ahmad and Tsuji (2021) used deep learning techniques, including CNNs, for vehicle identification and classification based on seismic data. They achieved a 96% classification accuracy using vertical-component seismic data.

Murugan et al. (2019) implemented a system for detection of automobiles, achieving a recognition accuracy of 91.3%. Shehata et al. (2019) have used Faster-RCNN for detection, CNN for classification, and motion vector estimation (MVE) for tracking.

Khan et al. (2022) utilized CNNs for detecting mishaps happened during traffic by using a Vehicle Traffic Surveillance System (VTSS) and achieved an accuracy of 82% using a rolling prediction algorithm.

Katanyoo et al. (2013) developed a system capable of detecting lane change violations and red-light violations. Their approach involves detecting vehicles and determining the status of the traffic light (red or not). By analyzing vehicle trajectories, they can identify violations accurately.

The experimental results of the study of Rao et al (2022) demonstrated that the proposed model had an accuracy rate of approximately 80%.

Table 1: Review of studies on deep learning techniques used in traffic surveillance

Author Name	Year	Deep Learning Technique	Accuracy
Kurniawan et al.	2018	CNN	89.50%
Fernandez et al.	2021	YOLOv3, YOLOv4, spatial association, KLT tracker	not specified
Ahmad and Tsuji	2021	CNN	96%
Murugan et al.	2019	Region-based CNN (RCNN)	91.30%
Shehata et al.	2019	Faster-RCNN, CNN, motion vector estimation (MVE)	not specified
Khan et al.	2022	CNN	82%
Vishnu et al.	2017	CNN, background subtraction, Gaussian mixture modeling	not specified
Srivatsava et al.	2011	Deep learning-based object detection	96.60%
Rao et al.	2022	Machine learning techniques	80%

2.3. Deep Learning Approaches for Extreme Climatic Conditions:

A CNN-based strategy was used by Zhang et al. (2020) to detect vehicles in hazy situations. In situations of dense fog, their model detected vehicles with an accuracy of 88.2%.

Li et al. (2021) developed a system for identifying vehicles in snowy conditions. On roads covered in snow, their model's detection and tracking accuracy was 92.4%. Wang et al. (2022) developed a model to identify pedestrians in low-light situations. The model detected pedestrians with an accuracy of 85.6%.

Further deep learning model was used by Liu et al. (2023) to recognize traffic signs in wet environments. Under conditions of heavy rain, its model identified traffic signs with an accuracy of 91.8%.

A deep learning-based method was created by Wang et al. (2019) to identify rainfall intensity from weather radar data. The model was able to predict different degrees of rainfall intensity with an accuracy of 92%, allowing for precise real-time monitoring and forecasting of rainfall.

Similarly, Zhang et al.'s study (2020) used a deep convolutional neural network (CNN) to identify and categorize storm patterns in satellite images. The model's 88.5% accuracy in classifying distinct storm types made it possible to track and analyze severe weather events effectively.

Lagorio et al. (2008) proposed a system based on a statistical framework to find out specific meteorological events using a mixture of Gaussians (MoGs) approach.

Nookola (2006) employed correlation coefficient analysis to figure out the relationship between various parameters of climatic conditions and traffic volume variability.

Arth et al. (2006) developed an algorithm that performs effectively in all climatic conditions but is sensitive to factors like shadows, occlusions, and camera motion.

Roh et al. (2013) investigated the impact of climatic settings on highway traffic, focusing on truck traffic as a model to enhance winter road maintenance programs.

Smids (2006) implemented a work using the Open Source Computer Vision Library (OpenCV) and concluded that the proposed method using statistical approach perform better in video surveillance, although some misclassification intervals were observed during rainy weather.

Nandhini and Parthiban (2012) developed an algorithm resistant to almost all weather and lighting conditions for video-based monitoring systems, including vehicle identification and classification.

Cheung and Kamath (2005) focused on robust background subtraction, an essential module for reliable video surveillance systems in urban traffic.

Khan and Ahmed (2022) created effective road weather and surface condition detecting systems by utilizing readily available data sources. Three weather conditions—clear, light snow, and heavy snow—as well as three surface conditions—dry, snowy, and wet/slushy—were the main targets of their attention. They used transfer learning to make adjustments to pre-trained CNN models like AlexNet, GoogLeNet, and ResNet18. With a remarkable detection accuracy of 97% for detection of weather conditions and 99% for surface condition detection, the ResNet18 architecture performed the best.

Using YOLOv4 and the Spatial Pyramid Pooling Network, Humayun et al. (2022) created an improved vehicle detection system that can identify cars in a variety of weather situations. The proposed architecture, based on CSPDarknet53, incorporates a spatial pyramid pooling layer and reduced batch normalization layers. The authors augmented the DAWN Dataset using various techniques to increase its size and make the detection more challenging. During training, the model achieved a mean average precision of 81% and successfully detected even the smallest vehicles in the images.

Chen et al. (2020) proposed a vehicle detection system that includes a visibility complementation module to enhance detection accuracy in various adverse weather conditions. For object detection in different weather conditions, deep learning models do not need to be retrained. In order to complement visibility, a dark channel prior and a convolutional encoder-decoder deep learning network with dual residual blocks are combined. The model known as YOLOv3 deep learning model for vehicle detection to evaluate the system using several surveillance footages. The results showed that the system achieved an average computational time of 30 frames per second (fps) and improved accuracy by approximately 5% in low-contrast scenes and 50% in rainy scenes.

Al-Haija et al. (2022) proposed a framework that utilizes transfer learning techniques and Nvidia GPU to evaluate the performance of three deep convolutional neural networks (CNNs): SqueezeNet, ResNet-50, and EfficientNet. The proposed model in the study were trained and evaluated on two weather imaging datasets, DAWN2020 and MCWRD2018, with six weather classes. ResNet-50 CNN model demonstrated the best performance in weather detection, achieving 98.48% detection accuracy, 98.51% precision, and 98.41% sensitivity.

Elhoseiny et al. (2015) developed a CNN-based weather classification model that achieved an 82.2% normalized classification accuracy for sunny and cloudy classes.

Chu et al. (2017) used cameras as weather sensors to estimate weather conditions from images, achieving a 58% average accuracy in classifying weather types.

Table 2: Review of studies on existing deep learning systems for traffic surveillance in extreme weather conditions

Source: Author

Author Name	**Year**	**Deep Learning Technique**	**Accuracy**
Zhang et al.	2020	CNN-based strategy	88.20%
Li et al.	2021	CNN-based framework	92.40%
Wang et al.	2022	Deep learning-based	85.60%
Liu et al.	2023	Deep learning model	91.80%

Author Name	Year	Deep Learning Technique	Accuracy
Wang et al.	2019	Deep learning-based	92%
Zhang et al.	2020	CNN-based	88.50%
Lagorio et al.	2008	Statistical framework	not specified
Nookola	2006	Correlation analysis	not specified
Arth et al.	2006	Algorithm	not specified
Roh et al.	2013	-	not specified
Smids	2006	Statistical approach	not specified
Nandhini and Parthiban	2012	Algorithm	not specified
Cheung and Kamath	2005	-	not specified
Khan and Ahmed	2022	CNN-based models	97% (weather), 99% (surface)
Humayun et al.	2022	YOLOv4, Spatial Pyramid Pooling Network	81% (mean average precision)
Chen et al.	2020	Visibility complementation module	~5% improvement (low-contrast), 50% improvement (rainy)
Al-Haija et al.	2022	Transfer learning	98.48%
Elhoseiny et al.	2015	CNN-based	82.20%
Chu et al.	2017	Camera-based	58%
Xia et al.	2020	Simplified ResNet-15	High recognition accuracy

Author Name	Year	Deep Learning Technique	Accuracy
Ibrahim et al.	2019	Deep CNN models	91% - 95.6%
Guerra et al.	2018	CNN models	68% - 81%
Biffin et al.	2019	CNN	87.20%
Schaefer et al.	2020	CNN	81.30%
Yin et al.	2020	R-CNN	86.90%
Chen et al.	2019	YOLOv3	88.20%
Zhang et al.	2019	Recurrent Neural Network	95.20%
Yilmaz et al.	2020	CNN	98.30%
Tourani et al.	2020	YOLOv3	95.05%
Yu et al.	2017	Deep LSTM	30%-50% improvement
Kumar et al.	2020	Hybrid model (LSTM and CNN)	99.50%

2.4. Research Gap:

Rashinkar et al. (2018) presented their work on the automatic traffic control system. Khan et al. (2022) explored anomaly detection in traffic surveillance videos using deep learning. A robust background subtraction with foreground validation was investigated by Cheung and Kamath (2005) for urban traffic videos. Roh et al. (2013) studied the effect of fog, and their interaction on highway truck traffic. Nookola (2006) conducted research on weather impact on traffic conditions and travel time prediction. The focus of study by Nandhini and Parthiban (2012) was on the automatic detection of vehicles during the night using bright pixel segments coupled to spatial temporal methods. Lagorio, Grosso, and Tistarelli (2008) presented their work on automatic detection of adverse weather conditions in traffic scenes. The usefulness and reliability of deep learning models in real-time traffic scenarios have not been sufficiently studied in the field of traffic surveillance with deep learning. While some studies have produced encouraging findings, more research is necessary to fully grasp how these models function in contexts with dynamic traffic. Further there is a lack of investigation into the integration of various data sources, such as sensor data and meteorological conditions, to improve the accuracy and dependability of traffic surveillance systems.

2.5. Summary:

A review of the literature on the use of deep learning techniques for automated traffic surveillance in different climates was presented in this chapter. The research on traffic surveillance using deep learning highlights the potential of these techniques to raise the precision and effectiveness of traffic surveillance systems. These experiments show how deep learning models may be successfully applied to tasks including vehicle detection, anomaly detection, and weather condition classification. The results of these research show that different neural network models, including CNNs, R-CNN, YOLOv3, RNN, and LSTM, are effective for use in traffic surveillance applications. High accuracy in object detection, categorization, localization, and traffic flow prediction tasks has been demonstrated by these models, demonstrating their potential to improve traffic management and safety.

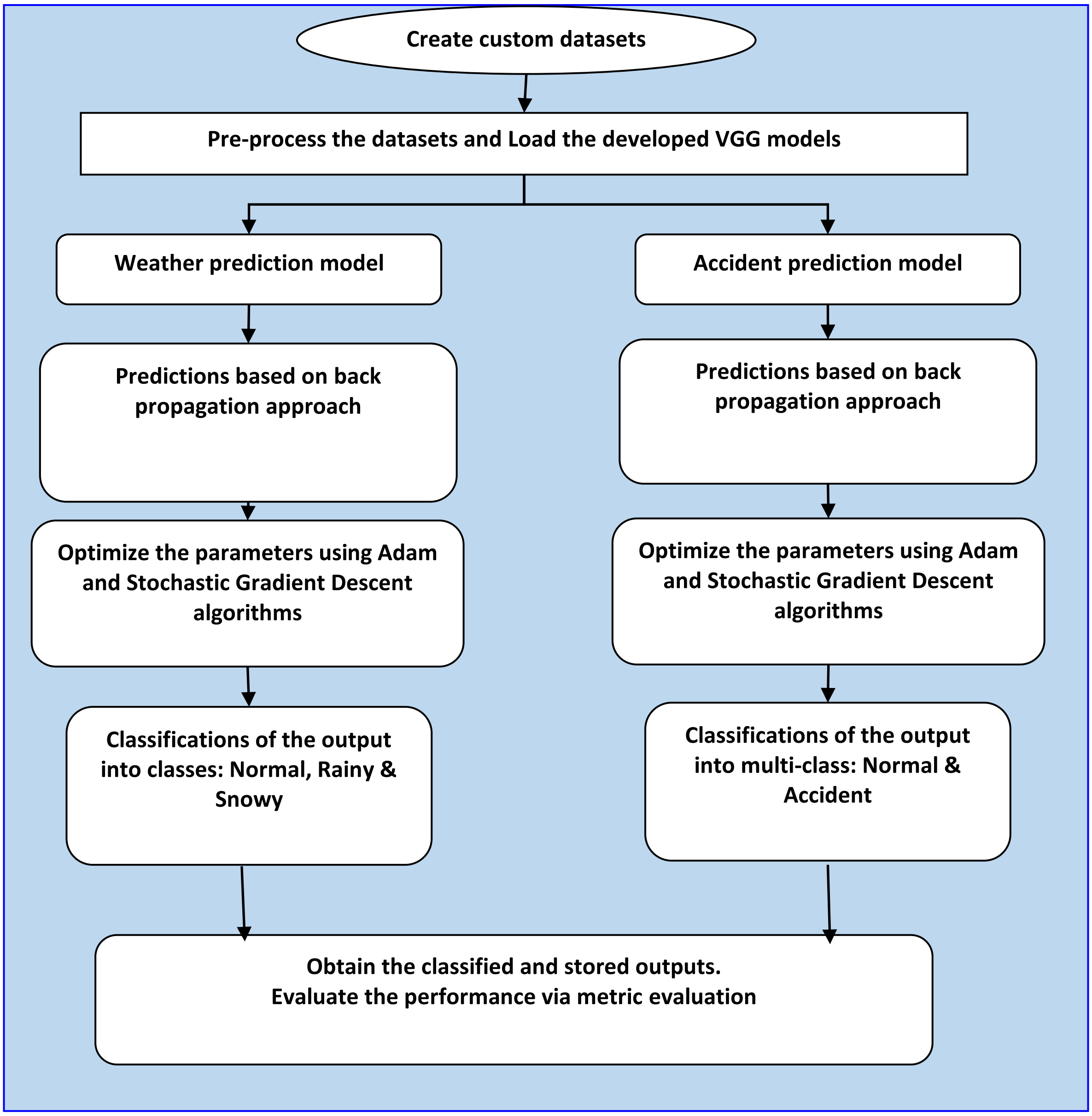
3 Research Methodology

3.1 Proposed scheme

The current research developed two VGG16 models in which a model predicts weather conditions and another predicts accidents. Both models use the same architectural layers and inputs where the output layers (features) alone differ. The research uses custom datasets created from the original dataset on car crash created by Bao, Yu and Kong (2020). The framework of the proposed research (refer figure 3.1) includes the flow of the research where the input images are pre-processed, passed onto the VGG16 models developed. The images are then segmented and focused by the computer vision algorithms adopted. To optimize the performance of the models developed optimization algorithms are applied. Finally, once the model is optimized the outputs are obtained, classified and stored respectively in the pre-defined labels/classes.

Figure 3.1: Proposed framework

Source: Author



The current research is unique, where the developed models use the same input for two different models. Existing studies have either developed a weather prediction model or an accident prediction model or a hybrid model to identify and classify the outcomes predicted.

In this study the researcher attempted to use the same input for two VGG16 architectural models that predicts and classifies the images into respective folders.

3.2 Proposed architecture

The proposed architecture is of Convolutional neural networks (CNN) with VGG16 model. The VGG16 models developed in this research has two approaches individually, namely: weather prediction and accident prediction. The accident that occurs during different weather as the concept has been adopted. Hence the same image as input is passed onto the two models simultaneously to predict the weather condition (snowy, rainy and normal) against the traffic accidents (normal and accident) classes defined.

Figure 3.2: Weather prediction model (WPM) architecture

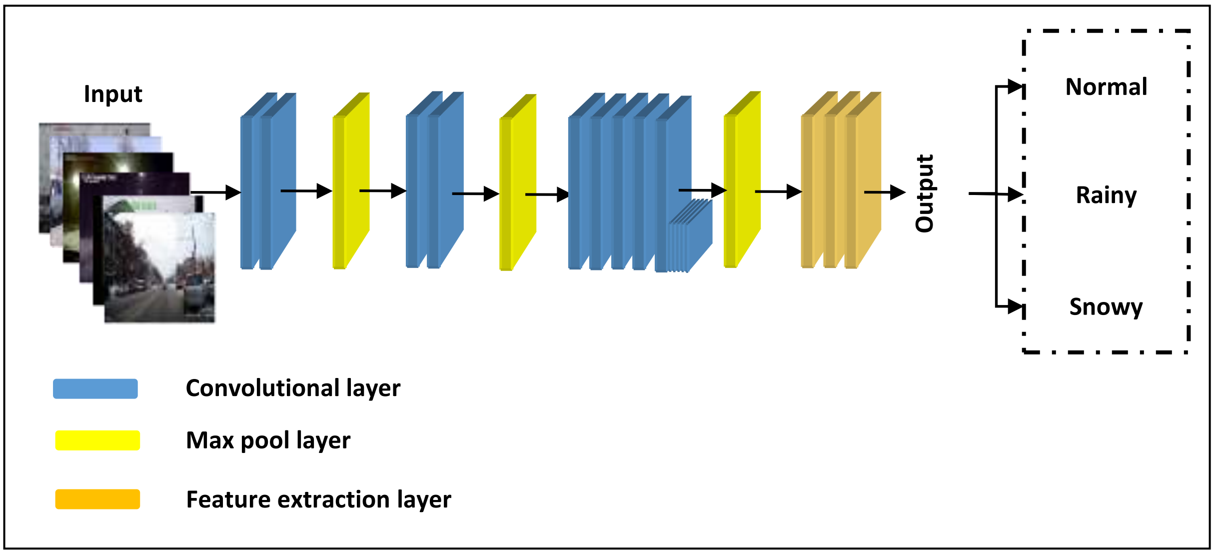
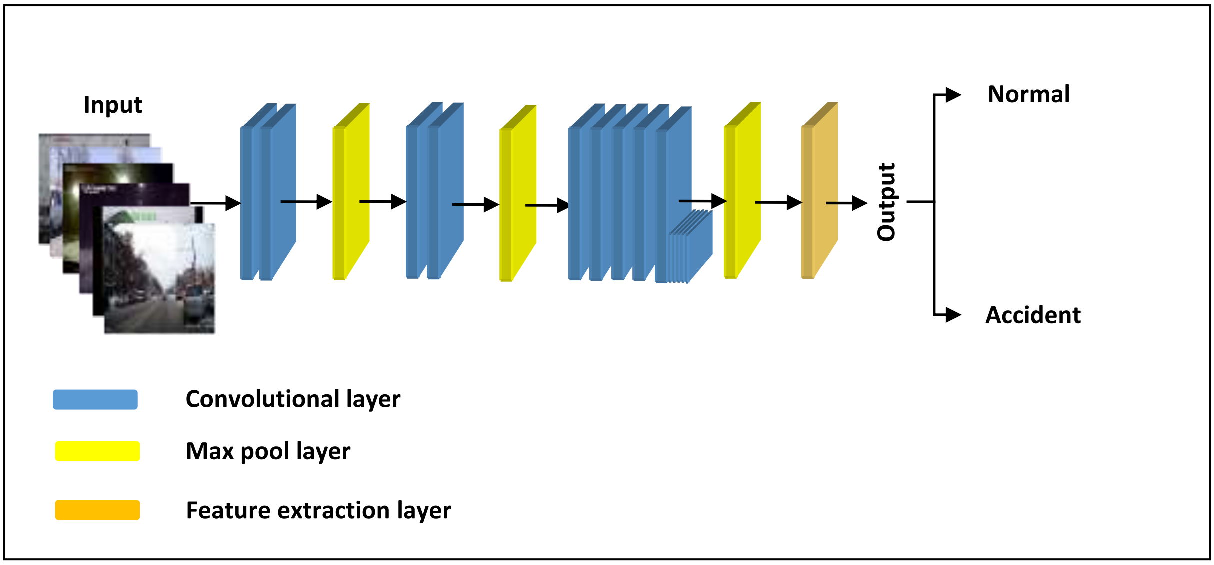


Figure 3.3: Accident prediction model (APM) architecture



The architecture for predicting the weather using the CNN+VGG16 layers includes input layer where the customized images as datasets are used. The images are pre-processed and the model is loaded, respectively. Both VGG16 models (WPM and APM) use the same networking layers where, only the feature extraction for classification based linear function layer is different in the models developed. The second stage is where the pre-processed data is passed through 2 x convolutional layers of sizes 64 each respectively; followed by a max-pooling layer in the third stage. Fourth and fifth stages are same as second and third stages where convolutional layers channels alone are different with 64 and 128 sizes, respectively. Followed by are 5 x convolutional layers of sizes 128, 256, 256, 256 and 512 respectively. The fifth convolutional layer is embedded with 5 x 512 sized convolutional layers (hidden layers); followed by is a max-pooling layer in the sixth stage. Finally, for feature extraction and classification the linear function layer is included. In the accident prediction model, there is just one classification feature in the feature extraction layer (refer figure 3.3) however in the weather prediction model there are three classification features in the classification layer (refer figure 3.2).

3.3 Algorithms adopted

The research uses the computer vision for image processing and thus the developed models uses the deep learning algorithms. Since the current research is based on prediction and classification of images (i.e. image recognition and segmentation) to classify them into respective classes/labels, it doesn't deal with forecasting or time series based algorithms. Hence pattern recognition is used here. To optimize the model, optimizers as algorithms are also adopted.

3.3.1 Adam optimization (AOA)

The Adam optimizer is adopted here to fine tune the parameters along with the Stochastic Gradient Descent (SGD) algorithm. The pseudo-codes used for the Adam and SGD as optimizer algorithms in this research are:

Algorithm 1: Adam optimization(AOA)

Step 1: Linear regression is used as input;

Step 2: Parameters are initialized;

Step 3: The variables are identified;

Step 4: Error values and the error differences of the expected and actual outcomes from training datasets are estimated;

Step 5: The deviations of partials are calculated namely w.e.ty0 and y1;

Step 6: Cost values are measured (number-values) and later applied the existing weights;

Step 7: Update the weights.

3.3.2 Stochastic Gradient Descent

To fine tune the model the research also utilizes the SGD algorithm, the pseudo-code is given below:

Algorithm 2: SGD

Step 1: To optimize learning-rate and initial parameters are required;

Step 2: Gather mini-batch samples from the training datasets;

Step 3: Set the SGD value as '0' for ***a***=1 to x do the gradient computation as estimation method, where SGD = SGD $\leftarrow SGD + \nabla_{\sigma} L(k(b^{(z)}; \sigma))$, $a^{(z)}$;σ.

Step 4: Apply the updates

Thus the optimizers are used and applied on the datasets, effectively towards improving the performance to attain higher accuracy and prediction rate.

3.3 Statistical methods and formulae

The statistical approaches adopted in this study are performance metrics and loss function to estimate the loss of the model. They are:

Loss estimation: Categorical cross-entropy as the loss estimation is used here. The loss is evaluated using the equation 1:

$$CC\ Loss = -\sum_{n=1}^{output-samplesize} c_n . log\ \hat{c}_n \qquad (1)$$

Performance evaluation metrics: By using the performance metric equations given below (2-5), the models' performances are estimated. The trp represents true-positives; trn represents true-negatives; faln represents false-negatives and the falp represents the false-positives:

$$Recall\ (Rec) = \frac{trp}{trp+faln} \qquad (2)$$

$$Accuracy\ (Acc) = \frac{trp+trn}{trp+falp+trn+faln} \qquad (3)$$

$$Precision\ (Pre) = \frac{trp}{trp+falp} \qquad (4)$$

$$F1-Score\ (Fscore) = \frac{2\ x\ Pre\ X\ Rec}{Pre+Rec} \qquad (5)$$

3.4 Dataset

The datasets used here are the customized data obtained as images captured from the videos collected and stored by Bao, Yu and Kong(2020). The database includes 1500 accidents-based videos, 3000 normal videos with different weather conditions. From these videos, the images are captured, pre-processed (re-sized) and used as inputs.

Data split ration: The customized datasets are split into 70:20:10 for training (70%), validation (20%) and testing (10%) respectively and used for evaluating the models' performances.

Image pre-processing: In the training phase of the models the image is resized as 299x299pixels. For the color adjustments (jitters) the brightness is set at 0.4, hue as 0.2, contrast as 0.4 and finally saturation as 0.4. Random flipping (vertical and horizontal) of the images are applied to the original images. The images are also resized and center-cropped in the validation and testing phases as 299x299pixel sizes.

Optimization: The learning rate (*lr*) is initially set as 0.001 with momentum 0.9 and decay factor at 0.1/7 epoch runs where the total epoch runs carried out is 25epochs. Later to optimize the model, the *lr* is fine-tuned as 0.0005 from 0.001 with 0.9 as momentum and 0.1 as decay factor (for every 7 epoch runs). The epoch runs are later increased from 25 to 60 steps.

4. Implementation and results

4.1 Implementation

The VGG16 models WPM and APM are developed to predict the weather conditions (normal, rainy and snowy) and accident occurrences (normal and accident) based classes. It requires a hardware setup with RAM of 8-16GB RAM, Intel Core i7 as the CPU/processor with NVIDIA GeForce as the GPU. The operating system (OS) like Windows 10, Ubuntu 16.04 and other advanced OS can be used which can access and install python 3.6 and Cuda 9.2, smoothly. The storage space in the local host should be of 1-4TB whereas the client side can be of server or the cloud (public and private). Libraries namely *pytorch* and *Tensorflow* in python is used. Minimum of 2 to 4GB memory is required for accessing, processing and storing the model and datasets.

The multi-class folders for categorizing the accidents due to weather are the normal, rainy and snowy. The research adopts the digital image processing where the images as digital copies are used as inputs unlike in the analogue where the hardcopies (photographs and printouts) are used as inputs. The models are tested in the host computer by testing the classes, the results are represented in tabular and graphical plots for both models.

4.2 Results

The epoch table (refer table 3.1) represents the 60 epoch runs carried out to heighten the accuracy and to reduce the model loss.

Table 3.1: Epoch values

Epoch	Train-Loss	Train-Accuracy	Test-Loss	Test-Accuracy
1	0.0110	0.7092	0.0119	0.4041
2	0.0110	0.7162	0.0113	0.4141
3	0.0110	0.7229	0.0115	0.4230
4	0.0110	0.7577	0.0115	0.4352
5	0.0109	0.7743	0.0114	0.4444
6	0.0109	0.8095	0.0112	0.4629
7	0.0106	0.8087	0.0107	0.5280
8	0.0093	0.8335	0.0096	0.6479
9	0.0086	0.8701	0.0089	0.7056
10	0.0086	0.8735	0.0090	0.7248
11	0.0081	0.8838	0.0084	0.7626
12	0.0077	0.8742	0.0078	0.7807
13	0.0077	0.8975	0.0086	0.7563
14	0.0073	0.8838	0.0078	0.7885
15	0.0067	0.8968	0.0074	0.8118
16	0.0067	0.8964	0.0076	0.8055
17	0.0066	0.8979	0.0068	0.8114
18	0.0065	0.8883	0.0065	0.8281
19	0.0065	0.8905	0.0075	0.8336
20	0.0064	0.8909	0.0073	0.8340
21	0.0062	0.8890	0.0067	0.8403
22	0.0063	0.8879	0.0065	0.8281
23	0.0062	0.8972	0.0071	0.8347
24	0.0064	0.8875	0.0070	0.8203
25	0.0063	0.8861	0.0064	0.8373
26	0.0062	0.8909	0.0071	0.8488
27	0.0062	0.8994	0.0072	0.8417
28	0.0062	0.8916	0.0069	0.8343
29	0.0061	0.8927	0.0063	0.8473
30	0.0059	0.8942	0.0068	0.8591
31	0.0063	0.8994	0.0064	0.8429

Epoch	Train-Loss	Train-Accuracy	Test-Loss	Test-Accuracy
32	0.0060	0.9020	0.0063	0.8458
33	0.0061	0.8901	0.0063	0.8580
34	0.0063	0.8901	0.0070	0.8425
35	0.0062	0.9027	0.0066	0.8362
36	0.0064	0.8935	0.0068	0.8247
37	0.0062	0.8805	0.0071	0.8395
38	0.0063	0.8997	0.0067	0.8462
39	0.0063	0.8942	0.0068	0.8451
40	0.0063	0.9001	0.0063	0.8466
41	0.0063	0.8883	0.0071	0.8454
42	0.0062	0.8994	0.0068	0.8406
43	0.0062	0.8894	0.0071	0.8377
44	0.0061	0.8886	0.0069	0.8569
45	0.0061	0.8931	0.0062	0.8491
46	0.0063	0.8920	0.0064	0.8347
47	0.0063	0.8949	0.0068	0.8343
48	0.0059	0.8972	0.0063	0.8536
49	0.0063	0.8838	0.0065	0.8480
50	0.0061	0.8960	0.0061	0.8414
51	0.0063	0.8957	0.0066	0.8388
52	0.0062	0.9001	0.0067	0.8421
53	0.0062	0.8883	0.0063	0.8406
54	0.0064	0.8942	0.0069	0.8366
55	0.0063	0.8886	0.0072	0.8462
56	0.0060	0.8931	0.0069	0.8488
57	0.0062	0.9012	0.0068	0.8340
58	0.0065	0.8964	0.0071	0.8218
59	0.0061	0.8972	0.0069	0.8499
60	0.0062	0.8872	0.0065	0.8443

Inference: From the epoch table (table 3.1), the obtained accuracy and loss shows that, as the epoch increases post optimization, the accuracy increased from 70% to 90% significantly with decreased loss value of 0.1 at the 60th epoch from the first epoch.

4.3.1 Accident predictions:

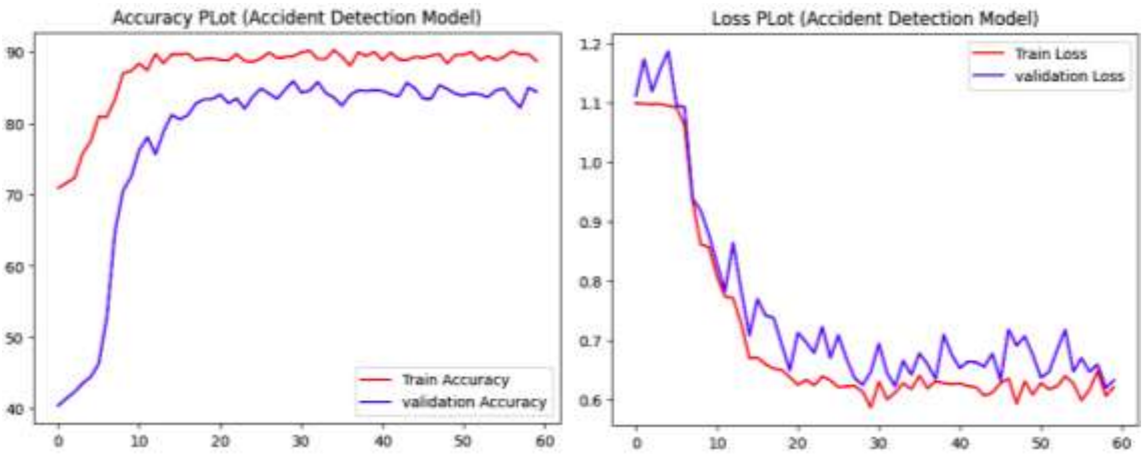
Table 3.2 Predictions by APM

S.No	Output	Actual class	Predicted class
1		**Accident**	**Accident**
2		**Accident**	**Accident**
3		**Accident**	**Normal**
4		**Normal**	**Normal**

S.No	Output	Actual Class	Predicted Class
5		**Accident**	**Accident**
6		**Normal**	**Normal**
7		**Normal**	**Normal**
8		**Normal**	**Accident**

S.No	Output	Actual Class	Predicted Class
9		**Accident**	**Accident**
10		**Normal**	**Normal**

Figure 3.4: Accident detection model - Accuracy (left) and Loss (right)



From table 3.2 of APM classifications, it is observed that the model is significant and effective in predicting and classifying the traffic accidents with the accuracy rate 90%. The APM model’s loss and accuracy are represented in the graph plots (refer figure 3.4).

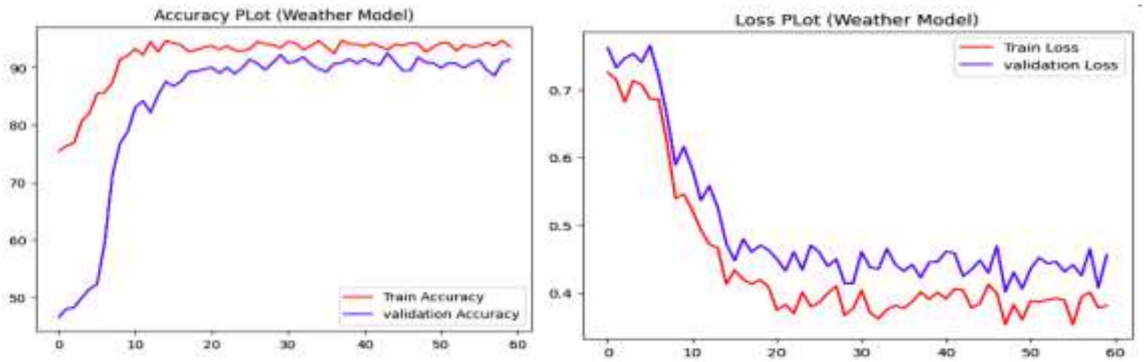
4.3.2 Weather predictions:

Table 3.3 Predictions by WPM

S. No	Output	Actual class	Predicted class
1		Normal	Normal
2		Rainy	Rainy
3		Normal	Normal
4		Snowy	Snowy
5		Snowy	Snowy

S. No	Output	Actual class	Predicted class
6		**Rainy**	**Normal**
7		**Snowy**	**Snowy**
8		**Normal**	**Normal**
9		**Rainy**	**Rainy**
10		**Rainy**	**Rainy**

Figure 3.5: Weather detection model - Accuracy (left) and Loss (right)



From table 3.3 of WPM classifications, it is observed that the weather predictions and multi-class classification model is more accurate in predicting and classifying the weather conditions like normal, snowy and rainy than the APM. The accuracy rate of WPM classifications obtained 92% where it is highly accurate for a multi-class classification. The WPM model's loss and accuracy are represented in the graph plots (refer figure 3.5).

Inference: Thus from the analysis and findings it is observed that, weather prediction model procured 92% classification accuracy whereas the accident prediction model procured 90% classification accuracy rates.

4.4 Performance evaluation

The performance is evaluated using the metrics and the results are represented in the tables 3.4 and 3.5.

Table 3.4: Accident classification report

	Precision	Recall	F1-score	Support
Normal	0.92	0.88	0.90	50
Accident	0.88	0.92	0.90	50
accuracy			0.90	100
macro avg	0.90	0.90	0.90	100
weighted avg	0.90	0.90	0.90	100

Inference: From table 3.4 it's observed that the APM model procured highest precision in the normal class and the highest recall rate in accident class.

Table 3.5: Weather classification report

	Precision	Recall	F1-score	Support
Normal	0.92	0.90	0.91	50
Rainy	0.94	0.92	0.93	50
Snowy	0.90	0.94	0.92	50
accuracy			0.92	150
macro avg	0.92	0.92	0.92	150
weighted avg	0.92	0.92	0.92	150

Inference: From table 3.5 it's observed that the WPM model procured highest precision and f1-score in the rainy class and the highest recall rate in snowy class.

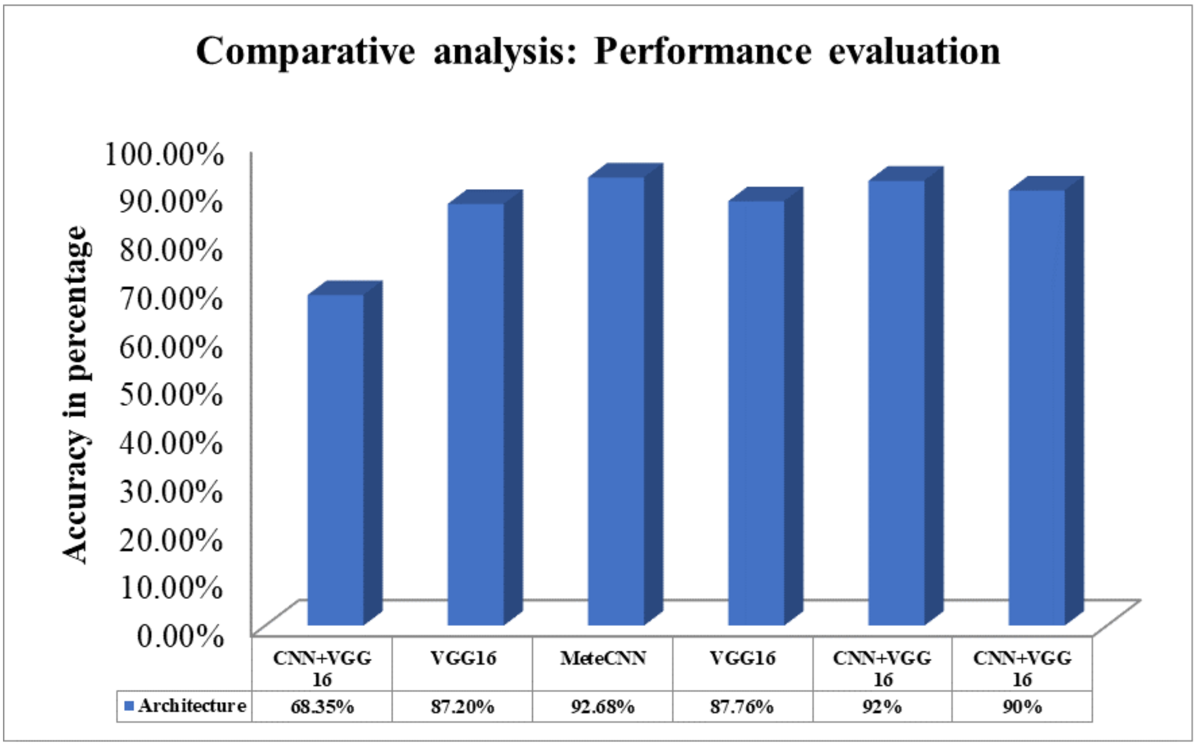
4.4.1 Comparative analysis

The comparative analysis in this research is carried out by examining the existing VGG networks and CNN architecture-based models with weather and traffic accidents based classifications.

Table 3.6: Comparative analysis

Author	Year	Architecture	Accuracy
Naufal and Kusuma	2022	CNN+VGG16	68.35%
Fridberg and Hoflin	2020	VGG16	87.20%
Xiao et al.,	2021	MeteCNN	92.68%
Xiao et al.,	2021	VGG16	87.76%
Proposed WPM	2023	CNN+VGG16	92%
Proposed APM	2023	CNN+VGG16	90%

Figure 3.6: Comparative analysis of CNN and VGG models in classifications



From table 3.6 and figure 3.6 it is evident that, the current models WPM and APM have procured higher accuracies than existing classification models of CNN and VGG based architecture.

5. Discussion and conclusion

The VGG16 application, also popularly known as the VGG-Net, is based on the VGG model. It is one of the CNN models, which supports 16 layers. CNN plays an important role in deep learning approach that can help classify, recognize, and forecast patterns in weather monitoring data (Kareem, et al 2021). Nonetheless, due to the inherent difficulties of such results, which differ greatly between datasets and systems, unstable CNN algorithms must be implemented and tested independently for each dataset and system. On the other hand, improved CNN models are required to eliminate error and present users with data that is almost comparable to the true value, and VGG6 will be an excellent option in addressing such challenges. The weather image has distinct qualities. Lighting, cloud conditions, rainfall, and snow all have an impact. This is a problem when identifying weather images that have commonalities between them. Foggy might look like snowy, and cloudy pattern might look like rainy. Image classification is one of the most recent technical disciplines that have the potential to replace human visual skills. Also, poor weather conditions might have potential consequences on various types of road accidents. Hence, predicting vehicle collision is also considered necessary. Snow has the greatest impact on single-truck collisions, whereas rain has a greater impact on single-car crashes. Of course, weather is not simply a direct determinant in collision risk. It also increases traffic volume, which is one of the primary variables associated with road collisions; usually, increasing traffic volume is associated with increased crash rates (Theofilatos and Yannis 2013). Detecting the accident prediction of car and weather monitoring before any accident happens is an essential duty for public health and road safety. A classification system on the basis of transfer learning has been suggested in this work employing deep learning architectures. The current research shows that employing VGG16 algorithms improves the efficiency of weather prediction applications since they are simple to implement. The current model obtained renders 92% accuracy in weather classification and 90% accuracy in accident prediction and classification.

In various cases, this model differed from existing high-performing models. First, it employed a small 3*3 receptive field with a 1-pixel stride, and these 3*3 filters worked together to deliver the function of a greater receptive field. The advantage of having numerous smaller layers rather than a single big layer is that the convolution layers are accompanied by more non-linear activation layers, which improves the decision functions and allows the network to converge quicker. Second, VGG employs a smaller convolutional filter, which essentially minimizes the network's propensity to over-fit throughout training. VGG16 is an object classification algorithm that classifies 1000 images into 1000 unique categories. Above all, it is an extensively acknowledged approach for image classification and is considered to be relatively easy to employ with transfer learning. As smaller filters cannot collect left-right and up-down information, a 3*3 filter can be considered the effective size. VGG is the smallest model that may be used to interpret the spatial aspects of a picture. The network is straightforward to operate because of the network's consistent 3*3 convolutions. Weather predictions are currently based on purely physical computer models, in which the atmosphere and ocean are governed by discrete numerical equations. While this approach has been proven to be very effective, current numerical weather prediction (NWP) models (Vogel, et al 2018) still have shortcomings for many important applications.

The weather condition is a significant component that is taken into account while making various decisions. Weather categorization is particularly effective in minimizing vehicle collisions. Manual weather categorization is considered inefficient and time-consuming. According to the study by Jiang, et al (2021), the proposed VGG16 model significantly outperformed the best-practice convolutional neural network for image classification, emphasizing that data augmentation can improve the accuracy of the model. VGG16 has been utilized in the categorization of weather images and transfer learning has been employed to accelerate the training of models in order to get higher performance faster (Naufal and Kusuma 2022).

The current model can be widely since it is capable of classifying weather phenomenon as well as occurrence of accidents. This model can be used for environmental monitoring and transportation, particularly in terms of weather change. Future research might explore the interaction of drivers' heart rate readings, low mental effort all through driving simulation, and exhaustion, as well as can use a driving simulator to carry out numerical analysis of heavy vehicle collisions.

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