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Classifying Road Conditions using Transfer Learning and Convolutional Neural Networks for Potholes and Smooth Surfaces

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Abstract— ***Pavement potholes pose a threat to both drivers and pedestrians. In many third world nations, it is a significant contributor to the tragedy that is traffic accidents, which often results in the loss of lives and property. So that vehicles may be alerted to alternative routes and the appropriate public authority can swiftly act to eliminate potholes for the advantage of travelers, it is necessary to regularly gather & refresh information on current road surfaces. Determine the proportion of road damage utilising the given factors: How deep the crater is. The highway has a lot of holes. To scare the government into action, rank the roads in order of importance, depending on which ones need fixing first. After signing up for an account on our hub, the user may submit a picture showing the location of a road along with some other metadata. When we have enough information, we'll create a database table that lists every street name and stores any user-submitted photos of that street. The ML model then makes a prediction of the percentage of damage. When calculating the proportion of damages to each indicated road, we will use an aggregate of the proportions shown in all linked pictures. A proportion of damage typical for that road type will be the end consequence. A straightforward and effective method for locating potholes on roadways is to use object identification techniques on photographs taken with a phone's cam. This project takes as its foundation a model of neural networks that has already been trained on a different set of data and then adapts it to perform the job of classifying road conditions. In order to improve performance and decrease the quantity of labelled data needed, models might transfer what they've learned from one job to another, a technique known as transfer learning. Image classification methods, such as the detection of potholes in road photographs, are ideally adapted for the convolutional network design.***

Keywords— CNN, Deep Learning, SVM, VGG, Pathole Detection

I. INTRODUCTION

In recent years, we've become used to very high levels of leverage; the highways and roads we use to get about are only two examples. Indeed, they link cities, towns, and even nations, making them the most popular form of secure transit. This heavy traffic, together with the effects of weather and other environmental factors, highlights the need of routine inspection and maintenance of our road systems. Even though we rely on them every day, the highways and roads we travel on are ultimately man-made & subject to flaws. If these roads aren't maintained, they'll eventually become hazardous, which will be inconvenient at best and even deadly for drivers and pedestrians alike. Use the following information to calculate the proportion of pavement failure: How many potholes there are, how deep they are, how common they are. Put out a thorough report for the administration outlining which routes must be repaired first and where they rank.

A pothole forms when the road surface deteriorates structurally. It can't be disregarded because of the potential for devastating road accidents it might trigger. According to a survey conducted in 2006 by the ADB, over 50% of the these pavements are in poor quality. Industrialized economies worldwide nearly universally face the same issue. Bad weather and the constant passing of large trucks are responsible for creating potholes. Accurately spotting potholes is the first and most crucial stage in maintaining the road's condition[1,2]. There has been a flurry of research towards automated pothole detection in recent years. Using a SVM was suggested by Lin J. et al. [3]. The entropy of the picture was developed to remove the image area, and then the pothole was located using basic kernel SVM.

This strategy worked quite well in identifying the target. Photographs of fractures and potholes are fed into a deep learning system that uses CNNs to identify the various types of damage. CNN was used to create a model that was immune to distortion caused by improper lighting and shadows[4]. Using CNN techniques on photos captured by smartphones, HiroyaMada et al. [5] created a system to identify road damage. They used deep learning algorithms on a massive dataset they collected to identify potholes. The road damage detecting system's promptness and precision met with my approval. Other researchers have used deep neural networkbased classification model [6] to distinguish between regular road photos and those with potholes. The system cannot classify anything unless it is given the pictures' characteristics. For this purpose, Crack-net [7] proposes a novel neural model specifically designed to identify road fractures. Unlike previous neural models, this one does not include pooling layers. This technique worked well for locating road flaws like cracks and bumps. Automatic fracture detection was suggested by ZhangL. using a deep Cnn architecture and several sensors[8]. There is no need for manual feature extraction operations in this model, since it can learn the characteristics on its own. Real-time pothole identification for Android was created by A.Tedeschi et al.[9].

In this research, we provide a method for doing so that makes use of machine learning and AI algorithms to produce a reliable and effective pothole detecting system. The Vgg Automated system, the SSD methodology, the HOG with SVM, and the Faster R-CNN are all state-of-the-art supervised learning models that are taught to see which prototype or ensemble of existing models yields the best results. Our pothole requisite knowledge and skills is divided into two sections: (1) data preparation, and (2) picture prediction for potholes using ml. First, we choose out the pieces of all the data that fit our model: the training data, the test data, the good photos, and the bad ones. The second step involves feeding the cleaned data to the deep neural algorithms that will make the pothole forecasts for training and testing. Finally, testing findings show that VGG is the fastest and most accurate method across the board for all item dimensions. When it comes to saving time, VGG still performs well.

II. LITERATURE REVIEW

Collaborative monitoring & pothole identification & activities were mainly at the cutting edge of the field are discussed here. At the conclusion, Table 1 provides a comprehensive evaluation of the accessible pothole better coping. For a long time, data gathering strategies for various city dynamics have placed a premium on data shows [28, 34]. Providing spatial quantities such as Coordinates or meteorological parameters (for example, heat, sound) is only one of its numerous applications [3, 43]. It is also employed in domains such as healthcare system, urban observation, and natural capital control. The authors of [20] create a programme called NoiseProbe that monitors noise pollution in metropolitan areas and displays the data in a way that is both graphical and temporally accurate. Less energy is wasted during dynamic event detection thanks to the authors of [33], who employed participative sensing. As such, they have developed two distinct methods, one using the SVM method, and the other using Minimal Cutting concept. To organise city streets, Nunes et al. [36] offer a crowdsourced sensing platform called Streetcheck. Information on the roads is gathered from many sources and then analysed, filtered, and categorised depending on what people have said. A diagram of a designated highways is shown further on. Portable and easily accessible smart objects are at the heart of these interactive sensing-based systems, which observe and monitor their surroundings in order to carry out a variety of activities.

As AI continues to advance, researchers are using a variety of machine learning algorithms [14,18, 35,54] in their efforts to identify and track potholes. In [1], a Phylogenetic Parametric Modeling based technique is created to get the likelihood of a fracture over each pixel in a pavement image. SVM is used to compute risk maps using multi-scale local information. Using metrics like accuracy, recall, and F1score, they show promising outcomes. Unfortunately, they were not able to give a method for detecting cracks in real time. In order to keep roads in good condition without breaking the bank, Hassan et al.,hassan2019road created a system that utilises sensors installed in moving cars. When comparing the True Good Performance of 4 distinct algorithms utilised for the classification, SVM came out on top with 95.2%.

They solved a problem for both road maintenance workers and motorists by creating real-time road maps of relevant abnormalities. However, since they've kept everything local, their system isn't expandable (SD card). Bhatt et al. [9] presented a final system that had used sensor data from gyroscopes and accelerometers to monitor road quality and identify hazards like potholes. They have used an SVM classifier to identify potholes, which would help city workers fix the damaged roadways. But the accuracy of their classification algorithm is just 93% when identifying traffic conditions and 92% when identifying pot holes. There is a system called VRNI [5] that uses GPS and velocity data through automotive to monitor road conditions in real-time.

Two OCSVM have been trained on horizontal and vertical speed data to identify damaged road conditions. All road imperfections, from tiny cracks to large potholes and bumps, may be detected using a single OCSVM model. In order to tell the difference between little dents in the road and major potholes, another OCSVM algorithm is used. Although they made progress in real time detection, they they did not develop a comprehensive strategy. Six distinct machine learning classifiers are presented for use in the real-time identification of road irregularities in [23]. They have tackled a multiclass classification issue utilising a variety of different methods. They have also made maps giving vehicles the routes with the fewest potential hazards. However, they failed to offer citizens with timely support. In order to determine the state of the roads, two different approaches have been offered by Cabral et cetera. One included detecting anomalies in roadways using KNN and the DTW method, while the other involved classifying concrete or dirt roadways using Svc, Lbp, % ResNet. Ultimately, they decided that SVM plus KNN- DTW performed better than the traditional KNN approach. However, no real-time method for tracking potholes was developed as a result of their efforts.

Applying a VGG detector developed by Suong et al. that relies on CNN as its primary algorithm, they were able to identify potholes in [48]. Since the VGG architecture only has 27 layers and 18 million parameters, it is more compact and less expensive to run than its predecessor. A technique for spotting road hazards, based on the VGG framework, was presented by Chitale et al. [15]. The technology analyses photos of both wet and dry potholes using a custom-built dataset. To further refine the assessment of the pothole's size, we use a triangle similarity metric based on image processing. The use of infrared radiation emitted from objects and measured to form a picture is another method for detecting potholes [8]. This is accomplished using thermal imaging. For the purpose of pothole identification, they've experimented on both custom-built Convolutional networks & a ResNet model that was pre-trained. Data pre-processing was the main focus of their study, and they did this by obtaining photographs of potholes utilizing thermal imaging equipment. It aids users in locating potholes at night by capturing photographs with the use of heat.

The authors of [38] suggest using a CNN model to detect potholes in a variety of weather situations. Very few researchers have utilised TL [7] in image classification, where a pre-trained model such as ResNet50, Inception-, VGG-19, and others is used to achieve high accuracy with very little quantities of data. Detecting pavement cracks using pre-trained models is a common practise, and in [39] the authors offer an approach depending on a refined discrete wavelet unit with additional regularise parameter. In [22], the authors present a deep CNN that was trained on the massive ImageNet dataset using VGG-16 as the which was before model. Their technology is 90% accurate in detecting pavement cracks, but they don't provide real-time identification.

Here , Table-1 compares the existing studies in depth across a variety of parameters, including speed, scaling, pothole mapping, end-to-end behaviour, real-time detection, and more. Using this table, you can easily see where there are significant gaps in the current research and where it falls drastically short in relation to the aforementioned criteria. When compared to these precedent works, our suggested method is distinct in the following ways: (i)The aforementioned works in the field of research concentrate mostly on the pothole detecting problem. In contrast, we provide a comprehensive end-to-end system for continuous monitoring & geographical mapping of pothole. There are other services that citizens, local officials, and government officials may access via this system. (ii)We present a novel Classification algorithm for pothole identification that outperforms all known methods (racy of 97.6%, Roc of 0.96). (iii)The suggested system, in contrast to the current efforts, offers a participative sensing type solution for citywide

Figure 1 Examples of training data

Figure 2 Examples of test data

Table 1 A detailed comparison of the existing road condition monitoring techniques in terms of major contribution, performance(accuracy, precision, recall, F1-score), scalability, real-time detection, end-to-end behaviour, and pothole mapping

Research Work	Reference & year	Contribution	Performance Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Scalable	Real-time Detection	Pothole-marked Map	End-to-End System
SVM	Dihao et al. [1], 2018	Pixel-Level Crack Detection using PGM & SVM.	–	90.7	84.6	87.0	×	×	×	×
	Anaissi et al. [5], 2019	road condition monitoring with two one-class SVM model.	97.5	–	98	97	×	✓	×	×
	Silvister et al. [45], 2019	Detect potholes with Mobile sensors & two-fold cross validation.	92.9	–	–	–	✓	✓	✓	×
	Hassan et al. [25], 2019	Low-Cost Road Maintenance and Road Quality Maps.	–	–	95.2	–	×	✓	✓	×
	Bhatt et al. [9], 2017	Used sensor data to detect potholes.	93	78	42	–	✓	✓	✓	✓
KNN	Cabral et al. [12], 2018	Classified paved and unpaved roads, detect road anomalies.	97	97	97	97	×	×	×	×
	Hameed et al. [23],	Used one versus all technique	–	–	95	–	×	✓	✓	×

Table 1 (continued)

Research Work	Reference & year	Contribution	Performance Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Scalable	Real-time Detection	Pothole-marked Map	End-to-End System
	2018	for Road anomalies detection.								
	Motwani et al. [35], 2020	Detection of dark edges as a pothole using KNN.	89	–	–	–	×	×	×	×
CNN	Suong et al. [48], 2018	Designed YOLOv2 architecture for pothole detection.	–	82.43	83.72	–	×	×	×	×
	Pereira et al. [38], 2018	Detection of potholes at various weathe r conditions.	98.8	100	99.6	99.6	×	×	×	×
	Anand et al. [6], 2018	Crack & pothole detection using texture based features.	96.93	–	–	73.14	×	✓	×	×
	Gopalakrishnan et al. [22], 2017	Pavement distress detection using transfer learning.	90	90	90	90	×	×	×	×

pothole monitoring in real time. (iv) Most current pothole monitoring methods donot offer a robust system in terms of geographic cover, file storage, etc. In this study, we used the cloud architecture to accomplish this scalability, which is a significant improvement over prior techniques.

Table 1 (continued)

Research Work	Reference & year	Contribution	Performance Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Scalable	Real-time Detection	Pothole-marked Map	End-to-End System
	Hanshan et al. [14], 2020	Detection of potholes based on location-aware CNN.	95.0	95.2	92.0	93.6	×	×	×	×
	Dhiman et al. [13], 2019	Pothole detection by stereo-vision analysis & deep learning.	–	88	84	–	×	✓	×	×
	Bhatia et al. [8], 2019	Used thermal imaging technique & with CNN and Resnet.	97.08	9.	9.	–	×	✓	×	×
	Wang et al. [54], 2019	Used surface normal information & CNN for road anomaly detection.	94.01	–	–	96.02	×	✓	×	×

III. METHODOLOGY

A. Transfer Learning

Vision - based practitioners often turn to enhance the learning experience as a means of shortening the development cycle for high-quality models. Using what we've learnt from one challenge and applying it to another is called "transferable knowledge." By doing so, we may save time and effort by building on earlier research and development. Because of the computing expense of developing such algorithms, it is usual practise to integrate and utilise models from existing literature. A which was before model is a mathematical system that's been built on a large test data to tackle a challenge comparable with the one we wish to address.

B. Convultional Neural Networks

Several big CNN-based pre-trained algorithms are used in domain adaptation. The rise in recognition of CNN in recent years may largely be attributed to the network's superior efficiency and straightforward training process. Standard fare for a CNN consists of two segments:

- The primary purpose of the completing is feature extraction, and it is implemented as a stacking of & pooling layers..

- The primary purpose of a classifier is to categorise the picture according to the observed attributes; classifiers are often made up of completely linked layers (layer where cells have effect of contact time to all activity in the preceding layer).

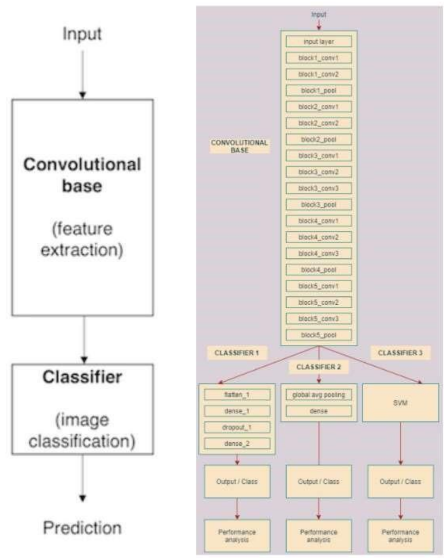

Fig.3. Architecture of our system

IV. PROPOSED PATHOLE DETECTION SOLUTION

A. Fully Connected Layers

In a neural network, a fully connected layer (sometimes called a dense layer) links each input node to each output node. In order to produce a prediction based on information from a convolution layers, they are often used in picture classification tasks. Fully connected layers may be used to the analysis of pathology detection characteristics collected from medical pictures. Typically, they are the final layer in a neural network, implemented after a succession of pooling and convolutional layers.

It is common practise to use a series of fully-connected levels immediately by a soft - max triggered level when solving picture classification challenges.
With the softmax layer's output of the likelihood function across each class label, we need just categorise the picture with the most likely class label.

Since every cell communicates with every other neuron, this layer type contains more parameters than any other.

Multiplying the amount of neurons in layer c by the number of cells in level p + biased factor yields the total set of variables. Therefore, the total number of variables is ((neurons in the following frame c * neurons in the previous layers p)+1*c).

Softmax Function:

$$\sigma(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \text{ for } i = 1, \ldots, K \text{ and } \mathbf{z} = (z_1, \ldots, z_K) \in \mathbb{R}^K$$

When given a vectors z of K actual figures as input, the softmax normalises the data such that the resulting likelihood function has K possibilities that are proportionate to the algebraic expressions of the input values.

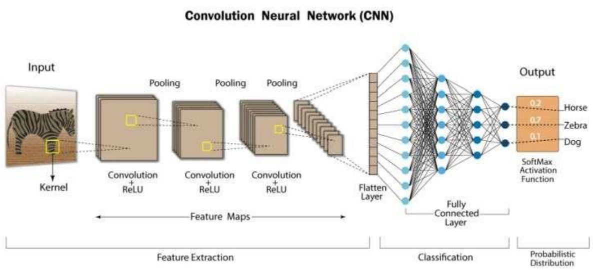

Fig4. OCNN Architecture

B. Global Average Pooling

Widely utilised in CNNs for image recognition tasks, average global pooling is a sort of pooling layer. The input image's spatial dimensions are reduced by the pooling layer, but the layer's essential elements are preserved.

The variables in the feature maps supplied are averaged together across all positions for optimal performance in global average pooling. Each feature map then has a single value, essentially limiting the input image's spatial size to one. Since fewer parameters mean less room for error, this may help curb overfitting.

The most relevant characteristics of medical pictures may be extracted via global average pooling, which can then be utilised for pathology identification. It may be used in a CNN as the last pooling layer after a succession of pools and convolutional layers.

To record the outcome of using the filtration to input, either the input picture or some other softmax layer, activated mappings (also known as convolution layers) are created. Understanding what aspects of the input are identified or retained there in feature maps is the goal of designing a visual representation of a previous layer for a given input picture.

It is common practise to apply pooling in 22 patches of the convolution layer with the a stride of on tw extracted features (2,2).

When using averaged pooling, the expected average of each convolution layer patch is determined. This signifies that the median value of both the squares (22) in the convolution layer is chosen.

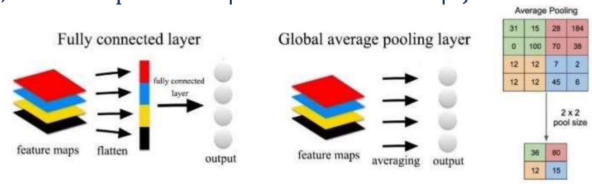

Fig.5. Global Average Pooling

C. VGG

Face identification, pedestrian detection, and traffic sign detection are just a few examples of the many applications for VGG, a real-time objects identification technique. To find and pinpoint holes in road photos, VGG might be utilised in this context. Since VGG just requires a single run through the network to provide predictions for all of the objects in the picture, it is considered a one-stage detector. The picture is broken down into a grid of cells, and inside each cell, the number of bounding boxes, the likelihood that they belong to different classes, and the reliability of each box's prediction are all predicted. In addition to its other benefits, VGG's ability to analyse a picture in under a second makes it ideal for use in real-time settings. With fewer parameters, VGG is less likely to overfit and is simpler to train.

Implementing VGG for road hole detection requires a collection of tagged road picture pairs. Next, the photos are put into the VGG network, which has been specifically trained to identify and pinpoint image gaps. By altering the network's design or the pre-processing of the photos, VGG may be made to function with various road images. For road photographs captured from a vehicle, VGG may be taught to identify potholes; for aerial images, it can be taught to identify holes in the road surface.

By adapting the architecture to anticipate the class of each pixel in the picture rather than merely bounding boxes, VGG may also be utilised for semantic segmentation tasks. Details regarding the holes' locations and sizes may become clearer in this way. Though VGG has its benefits, it also has its drawbacks. There are a few drawbacks, one of which is that it could not be as precise as other object identification methods, especially in cluttered settings or when dealing with little items. In low-resolution photos or when the holes are not clearly apparent or have a different form, it may also be less effective. Overall, VGG has the potential to be an effective tool for identifying road holes, particularly in realtime applications owing to its low processing time. However, its usefulness for a given job can only be gauged by measuring how well it performs on a test dataset designed for that purpose. We must remember that this endeavour may need model tweaking and the collection of a large and varied dataset for model training.

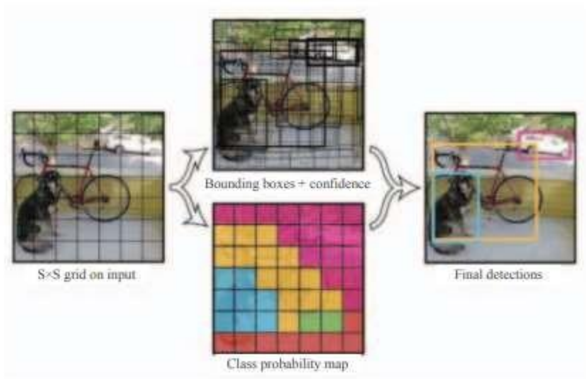

Fig.6. VGG architecture

D. Linear SVM

To classify data or predict outcomes, utilise a Linear SVM, a supervised ml technique. To determine whether or not a given road picture has a hole, Linear SVM may be used. As input, the method receives a collection of labelled pictures, each of which has been assigned a class label (such as "hole" or "no hole"), and uses this information to determine the location of a linear border between the classes. A fresh, unseen picture may be categorised based on the previously learnt boundaries. The use of image analysis and pattern recognition feature extraction is one method for implementing Linear SVM for hole detection in roadways. The SVM algorithm may take these characteristics as input. Using these characteristics, the algorithm will develop a threshold for distinguishing photos with holes from those without. Alternatively, the raw picture data may be fed into a linear SVM, which will then learn a threshold as in highdimensional feature space distinguishing images with holes from those without.

There are a number of benefits to using the Linear SVM algorithm to spot potholes in roads:

As a straightforward and effective approach, it performs well even with a limited set of training data. When compared to other approaches like neural networks, it is less likely to succumb to overfitting. The trained border can be easily interpreted, and it is clear which characteristics are crucial for classification. However, there are constraints with Linear SVM: When the openings are not easily detachable from the backdrop, a linear barrier may not be the ideal option. The algorithm's efficiency might suffer if the characteristics used aren't accurate representations of the basic hole design. Linear SVM may be used in tandem with other methods, such as computer vision and deep learning, to extract more useful features from pictures, hence boosting the algorithm's performance.

There are alternative object identification approaches that are more efficient and accurate, including such VGG or Faster RCNN, and it is possible that linear SVM is not the optimal strategy for this sort of work in reality. In general, Linear SVM may be a helpful tool for finding holes in roads, but it has to be tested on a dedicated dataset to see whether it is the best method. Train a sequential SVM predictor on the features collected by the way to deal to boost classification performance. If we consider a data point to be a domians vectors (a list of numbers), then we may ask whether or not a m - dimensional descriptor can be used to partition the points. A classification algorithm is what you get in this case. There is a wide variety of hyperplanes that might be used to categorise the data.

The optimal classifier might be the one that best illustrates the gap (or margin) between the two groups. So, we pick the hyper - plane such that the greatest possible distance separates it from the closest point on each side. In case there is such a subspace, we call it the highest higher dimensional space, and the nonlinear classification it provides is called an optimum predictor.

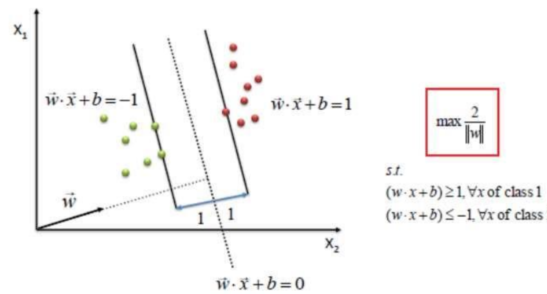

Fig.7. SVM

V.RESULTS

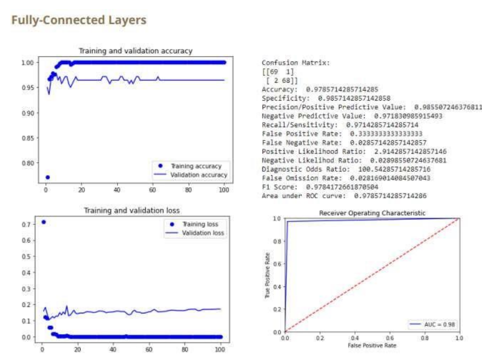

Fig.8. Analysis of FCL

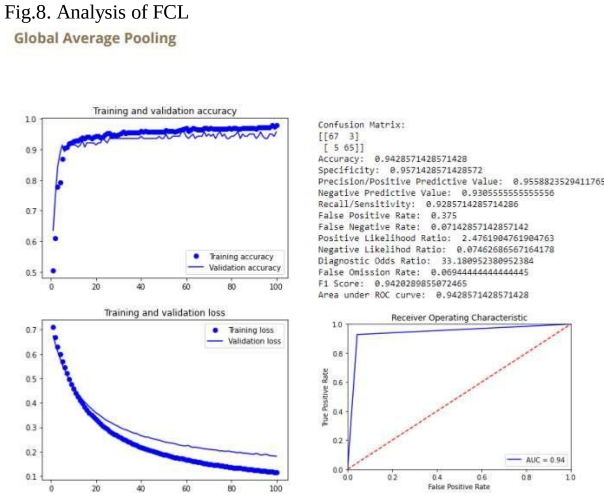

Fig.9. Analysis of GAP

Linear Support Vector Machines

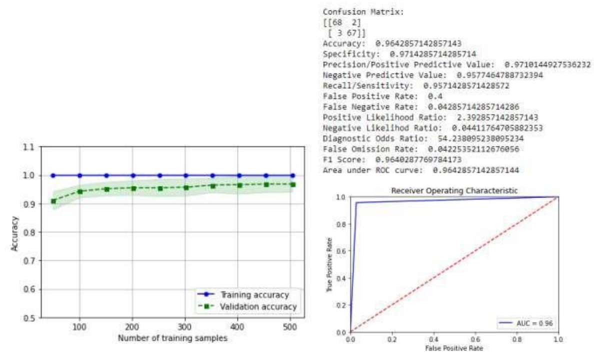

Fig.10. Analysis for Linear SVM

Comparison of the Accuracy of the Three Different Classifiers

	Fully Connected Layer Classifier	Global Average Pooling Classifier	Linear Support Vector Machine
Accuracy	97.86%	94.29%	96.43%

VI.CONCLUSION

As a result, we have introduced the ideas of transfer learning, CNN & pre-trained models in this project. The fundamental fine-tuning procedures for reusing a trained model have been defined. Explained a methodical process for determining the optimal fine-tuning technique, taking into account the dataset's size and degree of similarity. Added three more classifiers to utilise on top of the characteristics gleaned from the convolutional layer. And also Explained how the three different classifiers work and what they're good at. All three classifiers were analysed. Created ROC curves for each classifier and documented their respective performance.

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