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APPLYING MODERN CNN ARCHITECTURES TO BUILD AN EFFECTIVE FACE DETECTION MODEL

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Abstract

Facial recognition is seen as one of the big problems in computer vision. This field has received much attention due to the progress in artificial intelligence and deep learning. The availability of diverse data sets makes training of the models more accurate and as a result training of these models is important for the development of facial recognition systems in many industries as security and healthcare. The goal of this research is to develop an intelligent facial recognition system based on the pre-trained models DenseNet201, Darknet-19, InceptioResNetV2, and MobileNetV2, which are then fine-tuned in a supervised manner on a custom dataset in order to improve their utility. The research also adds to the body of knowledge on the accuracy and efficiency of these models for deployment in environments where speed and accuracy are paramount. Experimentation showed the DenseNet201 model to outperform the other models in terms of overall performance.

The model achieved exceptional results, attaining 92.75% accuracy, 86.09% precision, and a true positive rate (TPR) of 85.5%. Such outcomes demonstrate the capability of the DenseNet201 model and justify its selection for this research classification task, as it is trustworthy in feature and pattern extraction.

Key Words and Phrases: deep learning, face detection, Pretrained CNN Networks.

1. Introduction

Multimedia content is a part of our day-to-day life and has seen tremendous development in terms of variety and volume in the past few years. With the advent of technology, multimedia content serves as an integral part in numerous important sectors like education which uses this content to provide interactive and stimulating learning, social media which uses multimedia content as its core element of communication and expression and the business sector which uses creative marketing campaigns to sell their products and services. Multimedia is propelling the world into a more integrated and advanced digital society. Also Images and videos serve

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as the backbone of this content as they capture the attention of the users and provide information which turns them into a major focal point in digital marketing.

The set objectives of scientific research include improving the existing methods of dealing with visual data [1]. The scope of deep learning based image and video object detection systems is continuously augmenting [2] because of the vast possibilities of automation provided by artificial intelligence. This type of processing contributes to improving the ability to recognize objects with high accuracy and efficiency [3]. In most case, the purpose of the new deep learning model will prompt an appropriate network to be created. Often these networks and even trained networks will be applied to other tasks. Complex network models can also be constructed to cater to a wider variety of tasks, and these can be easily adapted for automated pretrained target detection through fine tuning to enhance specificity in recognition of additional objects.

With this approach, it is possible to take advantage of the general skills of available pre-trained networks and convert them into specialized tools that deal with the requirements of new tasks with great efficiency and without building a new model [4]. The detection and recognition of individuals using facial or body features as well as biometrics is one of the most important unresolved problems of computer vision, which has major uses in intelligent surveillance systems and automating vehicles. Nonetheless, these methods run into serious issues, including changes in body posture, obstacles, and lighting changes. Systems need to have precision in distinguishing people in busy places or in the detection of humans in restricted spaces. To address these issues, more advanced deep learning models that incorporate multiple sources of data are being developed. The objective in this field is the creation of intelligent systems that give effective security solutions and can perform in everyday and practical settings with precision. Thus, the value of increasing research directed at improving detection techniques through use of modern deep neural networks and machine learning to enhance the reliability of these processes. [5]

This area includes a number of critical applications such as: the automated identification of patients through image analysis and activity monitoring [6]; the automatic recognition of vehicles and drivers captured on CCTV cameras [7]. DarkCVNet increases the accuracy of pneumonia and COVID-19 detection by sharpening the model's differentiation of pathological features in X-ray images. This assists in faster diagnoses and less erroneous diagnoses [8]. Check identifying cars in surveillance cameras [9], also, it is used to assess feature fusion approaches with deep learning models for enhancing the identification of chest X-ray images done in relation to COVID-19, and so the model increases the accuracy of class distinction. [10].

The goal of this research is to design an effective and intelligent system that uses pre-trained models to perform face image detection and recognition.

The headshotimagesdetectionandrecognition_SOW.docx proposes that the models in this study will be optimized for performance and tested exhaustively against images belonging to the various categories as a measure of efficiency. Effectiveness will be evaluated based on the

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calculated metrics that stem from the confusion matrix pertaining to the models and thorough evaluation of their performance.

The advancements made into recognition of humans and vehicles drives research in computer vision, which is improving rapidly. Improvement of models in a particular area of study requires addressing a number of challenges first. Previous research has sought to enhance the precision and speed of the models. These attempts were found to be foundational.

Furthermore, vision scientists pose new efficacious and reliable system objectives, which optimates the accuracy of a system and enhances its dependability.

The goal of Muhammad Saqib et al, 2018, is to identify human heads in natural scenes captured in public datasets taken from Hollywood movies. In transfer learning, they leveraged a neural network with previously acquired knowledge. Their experimental results demonstrated that algorithms such as Faster R-CNN and SSD MultiBox with VGG16 surpassed YOLO [11]. Mehedi Hasan et al, 2021, proved the effectiveness of the VGGFace model based on ResNet-50 in enhancing the performance of the face recognition system. By employing multi-task convolutional neural networks for face cropping and using three KomNet datasets, the study claimed 94.41% accuracy with social media data and 100% with other datasets [12]. Benedicta Nana Esi Nyarko et al, 2022, performed an analysis on masked face recognition using the AlexNet, ResNet-50, and Inception-V3 models.

Findings of the study have demonstrated ResNet-50 model beats AlexNet (95.7%) and Inception-V3 (95.5%) with an accuracy of 97.5% [13]. Tapomoy Adhikari, 2023, tries to find the best method applicable to image recognition. The results illustrate that ResNet-152 was the most useful architecture with CIFAR-10 dataset (94.7%). These results, in fact, support the necessity of properly choosing the CNN architecture and training methods for very precise image recognition engagements. The author also adds the importance of the training technique with the BN addition to SGD leading to the result in [14]. Kinjal Ravi Sheth et al, 2024 used a fine-tuned transfer learning strategy with the pre-trained VGG16 model and the ND-IIITD dataset where face images were retouched and had ImageNet weights. With the TL VGG16 and using RMSprop as the optimizer, the model obtained a training accuracy of 99.54%, validation accuracy of 98.98%, and binary classification accuracy of 97.92%.[15]: In the same year, others, Heba Hamid Ali and collaborators studied face recognition systems adaptable with Internet of Things devices, based on EfficientNet-B4 model. The approach in this paper was based on transfer learning with fine-tuning to address the challenge of small data size while maintaining the model's remarkable accuracy.

Once the model was trained and saved, it was converted to a lightweight model, optimized for use in resource-constrained environments. The system was later installed on a Raspberry Pi for facial recognition. The results of the system were impressive, reaching an accuracy of 97%.[16]

2.Pretrained CNN Networks:

One of the essential principles in deep learning includes pretrained CNN networks, which refers to the process in which models are trained on large datasets to learn specific patterns and features. Most models work much better and faster when pretrained during some prior stage

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with features relevant to classification, recognition, detection, etc. Some important pre-training networks include DenseNet201, Darknet-19, InceptionResNetV2, and MobileNet V2. All these networks were developed to solve specific problems, however, all of them focus on improving the models when it comes to efficiency and precision in image processing and target detection. DenseNet is a convolutional neural network where each layer is connected to every other layer in the model making information flow more freely, resulting in fewer parameters, which makes it possible to easily achieve high accuracy image classification and vision tasks. In terms of speed, Darknet-19 outperforms many models as a result of the simple, yet powerful, lightweight architecture it is built on. The speed and efficiency of the network make it an excellent choice for image classification and object detection when they need to be done at a rapid pace.

Inception ResnetV2 is an example of a state-of-the-art architecture of deep convolutional neural network which is used for fine-grained image classification tasks. MobileNetV2 is a model that is based on convolutional neural networks and is light weight and optimized for mobile use, leveraging the Inverted Residuals class to aid in speed without sacrificing precision. These networks are geared towards optimally achieving one or several of these goals: increasing the accuracy of target detection, improving the processing speed, or achieving both. These networks allow users to take advantage of the numerous benefits offered by pre-trained deep networks whether in vision computer applications or other applications that need advanced levels of target discrimination and detection.

These are fundamental themes in making the best selection. present a table (1) comparing four renowned face recognition models, DenseNet, Darknet-19, InceptionResNetV2, and MobileNetV2. The comparison covers the number of layers, model size, accuracy, and speed of execution of each model. The table is intended to demonstrate the strengths and weaknesses of each model to assist researchers in selecting the most appropriate model for their purposes. Through this comparison analysis, an approximate equal per model can be established considering the performance, accuracy, and computations needed.

Table (1) a comparison of four popular face recognition models. [18, 19]

imagePretrainedNetwork Model Name Argument	**Depth**	**Image Input Size**	**accuracy**	**Speed of implementation**
DenseNet	201	224-by-224	very high	Relatively slow
Darknet-19	19	416-by-416	good	relatively fast
InceptionResNetV2	572	299-by-299	very high	Relatively slow

imagePretrainedNetwork Model Name Argument	Depth	Image Input Size	accuracy	Speed of implementation
MobileNetV2	53	224-by-224	v.good	v.fast

The pretrained image classification models DenseNet, Darknet-19, InceptionResNetV2, and

multiple criteria such as the depth of each model which is the number of layers in each neural network or model. It also shows the input size required for each model which is the size of the images that are fed into the model. The comparison is also based on the accuracy that the model gives since different models have different accuracy depending on the depth, the number of layers, and the complexity of the construction. It also shows the speed of implementation for each model which is important when one is considering a practical application especially in cases where the processing power is limited. The table also indicates the additional support package that is needed for each model.

This provides the user the option to select the model that is perfect for the project based on the need, whether it's the accuracy, resources, or in terms of efficiency. Figure (1) shows the block diagram of the proposed CNN-based detection model.

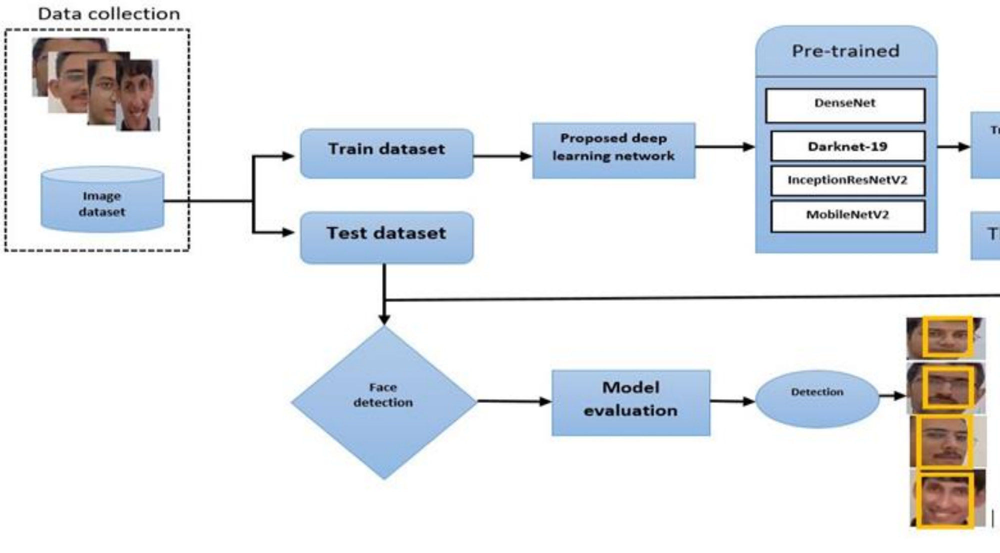

Figure (1) The block diagram of the proposed detection system using pretrained CNN networks

3.Methodology:

The field of deep learning has developed at an unprecedented pace, enabling the creation of pre-trained models that significantly enhance the performance of image analysis systems. Among these models are some of the most widely used CNNs, including DenseNet, Darknet-19, InceptionResNetV2, and MobileNetV2, which are utilized within the scope of this study for image classification, specifically for face detection and recognition. The advanced models

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of deep neural networks integrated within these networks allow for effective image processing and analysis.

This research centers on the application of face detection and recognition with the use of pre-trained neural networks that have been tailored on datasets with a variety of images. Once they are trained, the next step will involve testing the models on the test dataset and computing the confusion matrix as part of the evaluation analysis, along with benchmarking the results against the set objectives.

The purpose of the study is first to assess how different pre-trained networks such as DenseNet, Darknet-19, InceptionResNetV2, and MobileNetV2 perform, and then analyze the performance of the trained models to determine the model that accomplishes the best accuracy in face detection and recognition. The assessment will be done by evaluating the model's accuracy in face recognition under various conditions and comparing the results against other models. The chosen model will be the one that achieves the maximum error reduction and, correspondingly, maximum improvement of practical usability of the model. This part contains the main parts, I will discuss them one by one:

The tools software and dataset: This aligned with the objectives and the relevant tools of the performance were already provided. A Dell laptop was also used because it includes high technical specifications for computing and analyzing data efficiently. In addition, videos of human faces that need to be processed and analyzed by the system were captured using the iPhone and Samsung mobile phone cameras. The software that was utilized is MATLAB 2023b.

Creative dataset (facesuom2025) []: To facilitate testing, evaluation, and model training, a custom dataset called facesuom2025 was created specifically to assess and enhance the performance of deep learning algorithms for face recognition in this research. Data was collected by filming videos of four people at the Al-Mustansiriya University campus where the students were captured under different illumination and background settings to maximize the variability of the data. Subsequently, the videos shot were processed into multidimensional images, and each image was subjected to face extraction using face detection algorithms such as the Cascade Classifier technique, which accurately and swiftly identifies faces within images.

The database was organized into folders in a systematic manner. The first folder contains the original videos that were filmed. The training folder was organized into four subfolders, one for each individual, and contained 300 face images for each person from the segmented video footage. Furthermore, a test folder was created which contained four subfolders for each individual with 100 test images of their face. It was ensured that this data was crafted to meet the requirements of training and testing pre-trained networks like DenseNet, Darknet-19, InceptionResNetV2, and MobileNetV2, to assess how accurately the models could recognize faces in a local setting, see figure (2).

Figure (2) samples of the dataset (faces_uom2025) used in this study

Data was collected and people were assigned code as follows: Code A corresponds with Mustafa Tariq, Code B corresponds with Abdulrahman Mohammed, Code C corresponds with Sadiq Muhammad, and Code D corresponds with Lazem Kareem. There are 5 Epochs in the training process, which is the number of times the model was trained on the training dataset in order to fine-tune the model. After the training was completed with 80% of the data and testing with the remaining 20%, the resulting model was tested using the Confusion Matrix in order to determine the classification accuracy on different individuals. Confusion Matrix is a technique utilized in assessing the performance of classification algorithms in machine learning. It analyzes the errors made by the model in relation to the predictions and the actual results. Such an approach provides the precision needed for such a granular analysis of the results, where the errors that may arise from multiple classifications are found. In the testing phase, the rest 20% of the data was reserved for testing the model and evaluating its overall performance. At this stage, the accuracy of the pre-trained models to classify new images was tested.

The performance was assessed through various metrics such as accuracy and the confusion matrix which calculated how well the models classified individuals they were trained on.

Training was conducted on DenseNet, Darknet-19, InceptionResNetV2, and MobileNetV2. All models went through training with for epochs (5) at a learning rate of 0.001. Each model's training encompassed four facets, leading to four different neural networks for each of the models mentioned above. This is done to optimally configure the networks for the targeted dataset by adjusting the parameters of the models, which is done to ensure that all the models receive identical and impartial evaluation benchmarks.

A test database consisting of 100 images for each of the four subjects was prepared. After applying the trained models (DenseNet, Darknet-19, InceptionResNetV2, and MobileNetV2) to this test database, a confusion matrix was created for each model individually. The matrices helped evaluate the accuracy of the models with respect to the test data, allowing the determination of the capabilities and faults of the predictions made by the four models on the test dataset. The following algorithm illustrates the working of perplexity matrix algorithm:

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Input: Pre-trained neural network model (.mat), dataset testing
Output: confusion matrix, Accuracy, Recall/TPR, Precision
1.Initialize the environment: Clear variables, close windows, and clear warnings. Extract the date and time to create organized folders and files. **2.Load the pre-trained model:** Read a .mat file containing the pre-defined neural network (CNN). **3.Load the dataset (images):** Select the image folder and convert it to an imageDatastore using the folder names as categories. **4.Prepare the data:** Resize the images to fit the network input. Convert the black and white images to RGB if necessary. **5.Image classification:** Classify the images using the model. Calculate the time taken for each image. Calculate the overall classification accuracy. **6.Analyze the results:** Create a confusion matrix. Calculate the mean, minimum, and maximum confidence values (scores) for each class. Draw confusion matrices with this information and save them as images. **7.Calculate performance metrics:** such as accuracy, recall, precision, sensitivity, and F1-score. Output them to Excel and Word files. Example image display: Display random images from the dataset with the correct and predicted classification. **Saving results:** Save tables, images, and reports in a folder designated by date and model used.

4.Results and Discussions:

The DenseNet, Darknet-19, InceptionResNetV2, and MobileNetV2 models face recognition with impressive accuracy, arguably because of the large datasets on which the models were pre-trained. Despite the five epochs of training on the face classification dataset where attempts were made to fine-tune the models, there were several cases where training was completed successfully within two epochs with a perfect accuracy of 100%. This phenomenon might be

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as a result of pre-trained models having captured the canonical features of images during training on ImageNet and therefore responding very easily to novel data in epoch 2. This indicates that the model learned to generalize well, in turn, efficiently processing the data which led to a prominent level of accuracy obtained in the short amount of time.

The examined models have tested on the given face recognition dataset and compared in terms of accuracy, execution time, model size, and other criteria illustrated in figure 3.

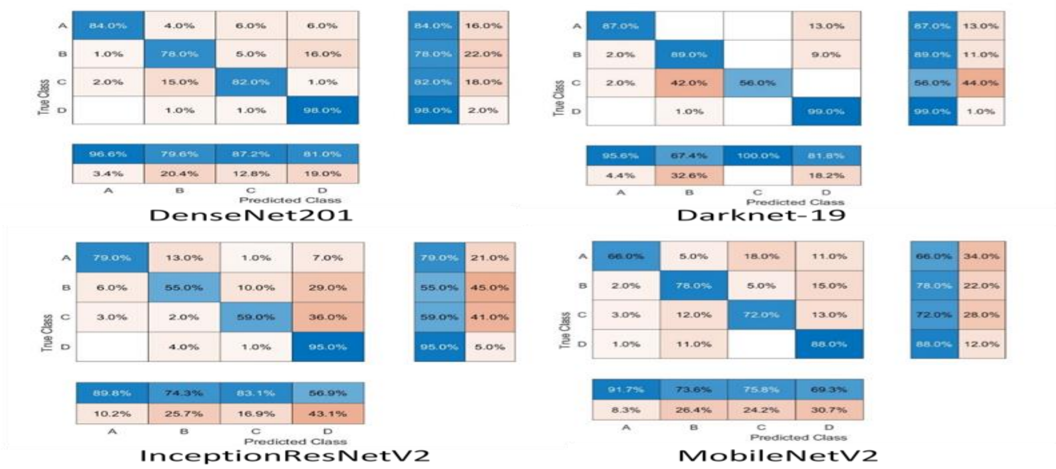

Figure (3) confuse matrix for the four proposed models

The confusion matrix presented in Figure (3) displays the results for the four models: DenseNet201, Darknet-19, InceptionResNetV2 and MobileNetV2, which were analyzed with respect to Image 1 (DenseNet201) With the highest accuracy for Class D: 98%. Classes A and C also perform well with 84% and 82% respectively. The overall performance is good for Class D. Second image (Darknet19): Class D is excellent: 99% , Class B is excellent: 89%, but Class C is somewhat weak: only 56%. This model is quite good for certain classes, but struggles with Class C. Image 3 (InceptionResNetV2): C: 59%, B: 55%. These middle performers also show a high error rate of around 41-45% for some classes. This model has the least balanced performance across all classes. Fourth image (MobileNetV2): balanced performance A: 66%, D: 88% - average performance with some confusion especially between A and C.

The strongest performer was the first image (DenseNet201): most accurately maintains the balance needed between classes, high accuracy in all classes (more than 78% for all classes), and lowest overall error rate.

This tabel 2 provides a comparison of the face detection and recognition process pre-training techniques. The prior assessments will help make a decision relative to the criteria at hand.

Table (2) Performance benchmark comparison for the proposed networks.

models	Precision %	Accuracy %	TPR %
DenseNet201	86.09	92.75	85.50
Darknet-19	86.21	91.37	82.75
InceptionResNetV2	76.02	86.00	76.02

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MobileNetV2	77.58	88.00	76.00

Table (2) provides a comparative analysis of four models with respect to their accuracy, precision, and total positive TPR (TPR) scores to assess their face classification and target class detection capabilities. The comparison includes four classification models: DenseNet201, Darknet-19, InceptionResNetV2, and MobileNetV2, focusing on precision, accuracy, and detection rate (TPR). From the analysis, it is clear that DenseNet201 outperformed all other models, surpassing them with an accuracy of 92.75%, precision, and TPR (85.5%) illustrating a balance between class recognition and erroneous classification. The other models performed relatively poorly, with Darknet-19 achieving similar but lower TPR scores and InceptionResNetV2 performing poorly on all metrics. These observations suggest that DenseNet201 is the most superior model in this comparison.

In assessing the performance and reliability of the models during training, learning curves which demonstrate accuracy over five training epochs were plotted as shown in Figure (4). It is observed that DenseNet201 performs exceptionally well from the first epoch onwards and by the second epoch, it rapidly stabilizes, surpassing an accuracy of 91%. This shows that it has a great capability for rapid face data recognition due to the pre-training on ImageNet.

On the other hand, the InceptionResNetV2 model fluctuated incredibly and took an unacceptable amount of epochs to yield reasonable performance which demonstrated poor speed within the context of other models. Both MobileNetV2 and Darknet-19 showcased slow but steady improvements alongside reasonable stability, failing, however, to outperform DenseNet201 in neither overall accuracy nor balanced performance. This analytics underlines the need for a model that not only provides high accuracy values but also achieves them rapidly during training for use in scenarios that utilize time-efficiency.

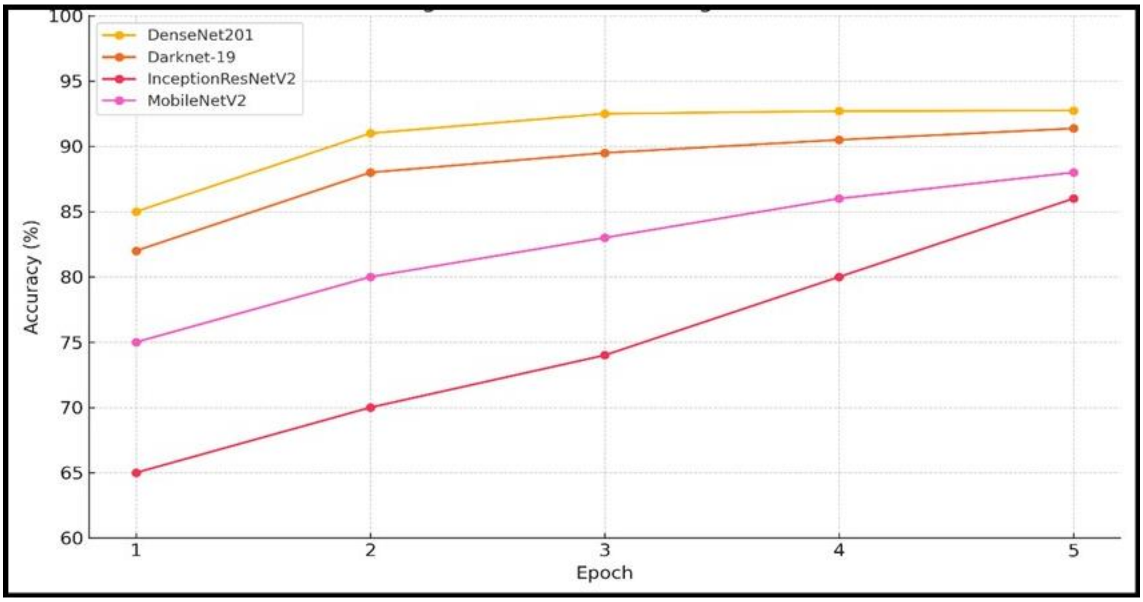

Figure (4) The estimat learning curve

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shows the accuracy evolution of each model over 5 training epochs. The accuracy progression during the five training epochs for all models (DenseNet201, Darknet-19, InceptionResNetV2, and MobileNetV2) is given in the figure and their learning curves.

It can be seen that DenseNet201 achieves a plateau by the second epoch which is an early plateau, while the rest of the models take more number of epochs. InceptionResNetV2 appears to have weaker learning oscillations than the other models.

Conclusion:

The evaluation results of the four convolutional neural networks (CNN) models: DenseNet201, Darknet-19, InceptionResNetV2, MobileNetV2 showed that DenseNet201 outperformed the others in data classification with an accuracy of 86.09%, overall accuracy of 92.75% and a correct detection rate of 85.5%. The second model Darknet-19 did not fall far behind and showed good results near denseand2 especially in accuracy 86.21% and a lower detection rate of 82.75%. On the other hand, InceptionResNetV2 and MobileNetV2 performed poorly, especially on the correct detection rate and overall accuracy, indicating their weaknesses compared to other two models. From this analysis, the models can be evaluated in order of most to least efficient as follows: first ranked is DenseNet201, followed by Darknet-19, then MobileNetV2 and finally InceptionResNetV2. Thus, with clear balance between precision, recall, and classification performance, denseand2 remains the optimal choice.

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