Applying Transfer Learning and Deep Neural Networks for Effective Health Prediction in X-Ray Data

202360131
Mahmud Dawjee
mahmud.dawjee.2022@uni.strath.ac.uk

202364269
Suvetha Gopal
suvetha.gopal.2022@uni.strath.ac.uk

202362889
Sania Irum
sania.irum.2022@uni.strath.ac.uk

202378171
Aziz Tarek
aziz.tarek.2022@uni.strath.ac.uk

***Abstract*— The purpose of this study is to examine the application of deep learning techniques, especially transfer learning utilising VGG16, MobileNetV2, and a Convolutional Neural Network (CNN), in predicting health issues from chest X-ray pictures, specifically identifying pneumonia and normal cases. The problem of restricted data availability in some fields encourages the usage of transfer learning, which involves reusing pre-trained models to reduce computing costs and improve model performance. Transfer learning models like MobileNetV2 displayed broad generalisation and high accuracy in detecting pneumonia by using encoded representations from preceding operations, but VGG16-based models continually performed poorly, unable to acquire significant patterns. The CNN construction produced promising early results but fluctuated during training, indicating possible overfitting or pattern capture concerns. These findings emphasise the importance of model architecture and training strategies in addressing data availability challenges in deep learning applications, emphasising the need for intricate adjustments and dataset quality enhancements for improved diagnostic accuracy from medical images.**

***Keywords*—Transfer Learning, CNN, DNN, VGG16, MobileNetV2, Xray Dataset, Health Prediction, Confusion Matrix, Comparison Study**

I. INTRODUCTION

A. Transfer Learning

One of the most significant methods in the field of deep learning is transfer learning. It entails repurposing a pre-trained model—one that was created for a certain goal—for an unrelated but distinct activity. When there is a lack of data available for the new work, this method is quite helpful. The capacity to apply the information acquired from addressing one problem to another that is similar but distinct is what makes transfer learning useful. This not only reduces the amount of time and money needed to train models from scratch but it also frequently results in improved performance, particularly for difficult tasks like voice and picture recognition. Three architectures are often utilised for transfer learning, but three stand out in particular because of their popularity and efficacy: VGG16, EfficientNetB0, and ResNet-50, as well as their corresponding variants (Yang & R, 2023).

1) Problem statement

Effective model training is difficult in the field of deep learning, particularly when dealing with small amounts of data for certain tasks. For traditional methods, training models from scratch frequently necessitates large amounts of data and powerful computing power. The answer to this problem is transfer learning. It entails reusing previously trained models that were first created for a single job to serve as foundations for additional tasks, especially in situations when the amount of data available for the additional tasks is constrained. This method is quite helpful in cutting down on computational expenses and training time while enhancing model performance. In the context of transfer learning, this problem statement focuses on investigating and using the capacities of well-known deep learning architectures such as VGG16, and MobileNetV2. These designs are well-known for their distinctive qualities and versatility, which makes them excellent choices for applications involving transfer learning. The objective is to comprehend how these learned models may be modified and optimised for novel, associated assignments, therefore tackling the difficulties associated with limited data and resource-intensive training procedures in deep learning. (Simonyan & Zisserman, 2015)

2) Research Questions

- What are the specific improvements in training efficiency and model accuracy achieved by employing transfer learning with architectures like VGG16, EfficientNetB0, and ResNet-50 in deep learning tasks with limited datasets?
- How does the transferability of features from pre-trained models such as VGG16, EfficientNetB0, and ResNet-50 vary across different domains and tasks in deep learning, especially in scenarios with data scarcity?
- Which transfer learning strategies are best for optimising the architectures of VGG16, EfficientNetB0, and ResNet-50 to maximise performance in novel tasks with scarce data?

- What effects does the selection of a pre-trained model (e.g., VGG16, EfficientNetB0, ResNet-50) have on the ability to perform and generalise deep learning tasks, especially when there is a shortage of training data?
- Can novel approaches to transfer learning using models such as VGG16, EfficientNetB0, and ResNet-50 result in the creation of more resilient and effective deep learning systems, particularly in environments with limited resources?

3) Rationale for Addressing this Application.

In situations where data scarcity is a major challenge, the integration of transfer learning with cutting-edge architectures such as VGG16, EfficientNetB0, and ResNet-50 represents a significant advancement in the field of deep learning. This strategy is becoming more and more important because deep learning models that are accurate and efficient are needed in a variety of industries, including digital assistants, autonomous vehicles, healthcare, and environmental monitoring. It is frequently impractical or prohibitively expensive to collect large datasets in these domains. Transfer learning solves this problem by making it possible to use previously trained models that are modified for new tasks, avoiding the need for a significant amount of training data. This significantly reduces the obstacles to implementing deep learning solutions and guarantees high accuracy in model performance, particularly in regions where data is scarce.

Furthermore, in transfer learning, architecture selection is very important. Models with distinct advantages include VGG16, which is well-known for its simplicity and depth, EfficientNetB0, which strikes a balance between accuracy and efficiency, and ResNet-50, which can train deep networks efficiently. A better grasp of these architectures' applicability for particular uses is facilitated by investigating how to use and modify them in transfer learning. This research is essential to creating more focused and effective models that are adapted to the unique needs of various tasks. In the end, using transfer learning with these complex architectures advances deep learning technology while also democratising its use, increasing the accessibility and usefulness of powerful deep learning tools across a wide range of industries (Gupta & Sinha, 2022).

B. Deep Neural Networks

Along with many other fields of research and applications, Deep Neural Networks (DNNs) have revolutionised picture classification. Due to their remarkable ability to learn intricate patterns and traits from simple inputs, artificial neural networks such as these are ideal for tasks such as picture categorization. Autonomous driving, medical diagnostics, item recognition, and many more fields have found applications for DNNs.

1) Overall Problem Statement

The creation and assessment of models using deep neural networks (DNNs) for picture classification tasks constitute the overarching issue that this study seeks to resolve. A wide range of applications rely on image categorization, including autonomous driving, medical diagnostics, object identification, and more. The efficiency and precision of a solution are heavily influenced by the choice of DNN architecture for a given picture categorization task (Ma Han & Wang, 2020). So, in the context of picture classification, this study intends to examine and contrast the efficacy of various DNN designs, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Autoencoders, Transformers, and Long Short-Term Memory networks (LSTMs).

2) Research Questions:

- Which deep neural network architecture is the most suitable for image classification tasks, and under what conditions?
- How do different hyperparameters and network configurations affect the performance of various DNN architectures for image classification?
- What are the trade-offs between accuracy, computational efficiency, and model complexity when selecting a DNN architecture for image classification?
- Can transfer learning techniques be leveraged to improve the performance of DNNs in image classification tasks?
- How does the size and quality of the training dataset impact the performance and generalization ability of different DNN architectures in image classification?

3) Rationale for Addressing this Application:

A major area that has been profoundly affected by the rise of deep learning is computer vision, particularly DNNs. Picture categorization is one area where DNNs really shine because of their incredible ability to learn complex and abstract characteristics on their own from raw data. Applying deep learning to the picture categorization issue might greatly help automated systems in numerous fields (Li et al., 2023). There is a wide variety of DNN designs available in the deep learning community, each one optimized to address a specific problem. Researchers and experts in the field must be aware of the best architecture for various picture categorization jobs. Trying out a few various designs until you discover the one that suits your needs could end up saving you a lot of time and energy. While DNN design is critical, hyperparameters and network settings are equally important for performance. We could learn a lot by studying how these hyperparameters affect DNN performance. Deep learning models may be trained to do better on picture classification tasks if our study improves model design choices and optimization methodologies (Duan, 2019). Problems with memory and processing power are common in real-world DNN implementations. It is crucial to take computing efficiency and model complexity into account. Further research in this area might lead to more efficient and accurate models, expanding the practical applications of DNNs. Deep neural networks (DNNs) may use the expertise of models trained on massive datasets to accomplish tasks with less labelled data by using transfer learning approaches (Ma Han & Wang, 2020). For data-constrained image classification tasks, which are common in many sectors, this might lead to DNNs becoming more widely available and affordable. The performance and generalizability of DNNs in image classification tasks are greatly affected by the amount and quality of the training dataset. Consideration of how various DNN systems deal with imbalance and noise is vital.

C. Literature Review

A review of the literature reveals a growing trend towards medical image analysis using deep learning and artificial intelligence. A number of medical specialties have shown promise for CNNs and Transfer Learning, including radiology, dermatology, and ophthalmology. Recent studies have shown promising outcomes when using convolutional neural networks (CNNs) for the problem of pneumonia detection, due to the networks' exceptional ability to extract and learn features from X-ray images (Rachburee & Punlumjeak, 2022; Zhao et al., 2023). Unfortunately, research comparing different deep learning approaches is lacking, especially in the healthcare sector. This study intends to address that knowledge gap by applying these models to a real-world setting and evaluating their efficacy. Healthcare is one sector that has been significantly impacted by deep learning, a branch of artificial intelligence and machine learning. Diagnostic imaging using this technology has changed the game for researchers and patients alike. It has the potential to drastically change diagnostic procedures and patient outcomes, as pointed out by Zhao et al. (2023). Deep learning algorithms, like CNNs, outperform conventional machine learning methods when it comes to picture identification. According to Hoar et al. (2021), healthcare organisations may greatly benefit from deep learning's ability to improve diagnostic accuracy, predictive analytics, and personalised treatment.

When it comes to medical imaging, however, using deep learning isn't without its obstacles. Concerns about dealing with huge datasets and the lack of annotated medical records are explored in depth by Alzubaidi et al. (2020). Making sure these models adapt to new settings is still a big hurdle to overcome. To overcome these obstacles, cutting-edge techniques such as Transfer Learning and specialised networks such as CNNs are required. According to Zhang et al. (2021), transfer learning is essential for transferring pre-trained models to new, more targeted tasks, which helps overcome the limits of healthcare data. Because there aren't many big, annotated datasets in medical imaging, this strategy is great for that field.

The research conducted by Rachburee and Punlumjeak (2022) found that medical image analysis using CNNs is advantageous, especially when it comes to X-ray pneumonia detection. Their results show that analysis of these pictures by convolutional neural networks (CNNs) may lead to improved diagnosis accuracy and the acquisition of new information. It shows great promise in employing models trained on big datasets, such as ImageNet, with features like VGG16 and MobileNetV2. Image feature extraction is a perfect fit for VGG16 because of its deep representation and high computational intensity. Gulzar (2023) argues that MobileNetV2 is more suited to low-power and mobile applications because of its optimisation for speed and resource efficiency. According to Gulzar (2023), this discovery may have far-reaching consequences for public health, which is why it is so important. It is crucial to get a correct diagnosis quickly since pneumonia is a major cause of sickness and death, particularly in susceptible groups. More efficient healthcare delivery and better treatment results may result from using AI to increase the precision of diagnosis. Advancements in artificial intelligence have the potential to revolutionise medical diagnostics and other aspects of healthcare decision-making. The use of deep learning and AI is becoming more common in several fields of medical picture analysis, according to the literature. However, studies comparing various deep learning algorithms in healthcare-related topics are very rare. This research intends to address that knowledge vacuum by evaluating and using these models in real-world healthcare diagnostic processes.

The significance of this research stems from the possibility that it will have an impact on public health. As a prominent cause of sickness and mortality, particularly in younger and older populations, an accurate and timely diagnosis of pneumonia is critical (Gulzar, 2023). Artificial intelligence that enhances diagnosis accuracy might result in improved treatment results and more effective healthcare delivery. Artificial intelligence (AI) has huge potential to transform the diagnosis of illness and establish the way for AI to be used more widely within medical choice-making. The core objective of this study is to use X-ray images to develop approaches for determining conditions, specifically in the context of a pneumonia diagnosis. Since untreated pneumonia can be fatal, a prompt and accurate diagnosis is absolutely essential. Because of this, this application was chosen (Rachburee & Punlumjeak, 2022). X-ray imaging is commonly used to detect pneumonia; however, these pictures can be varied and difficult to interpret. This work attempts to apply deep learning algorithms to improve the diagnosis process, reduce the likelihood of human mistakes, and maybe provide more accurate diagnoses (Gulzar, 2023). The application of AI here is also consistent with the larger objective of introducing cutting-edge technology into medical services in the hopes of enhancing results and patient care.

II. METHODOLOGY

A. Scope of Study

The purpose of this project is to employ deep learning techniques, notably transfer learning algorithms like VGG16 and MobileNet V2, alongside a Convolutional Neural Network (CNN), to predict a patient's health condition. The primary intent of the study is to study a collection of chest X-ray pictures in order to foretell medical conditions, particularly pneumonia and normal instances.

B. Dataset Details

As part of standard clinical treatment, children receiving care at Guangzhou Women and Children's Medical Centre between ages of one and five provided these photographs (Kermany et.al., 2018).

The typical chest X-ray in Figure II.1 (left panel) shows clean lungs with no spots of bizarre shading. Bacterial pneumonia (centre) is characterised by localised lobar grouping, in this example in the right upper lobe (white arrows), whereas viral pneumonia (right) is characterised by a more widespread "interstitial" appearance in both lungs. To train their AI system, researchers gathered and labelled 5,232 chest X-ray pictures from children, consisting of 3,883 characterised as developing pneumonia (2,538 bacterial and 1,345 viral) and 1,349 normal from a total of 5,856 patients. For evaluation, the dataset has 234 normal pictures and 390 pneumonia images from 624 individuals (242 bacterial and 148 viral). The three primary subsets of the dataset are called "train," "test," and "val," and they each contain subfolders for the two picture categories of "Pneumonia" and "Normal." Combining these two categories, it has 5,863 JPEG X-ray pictures altogether.

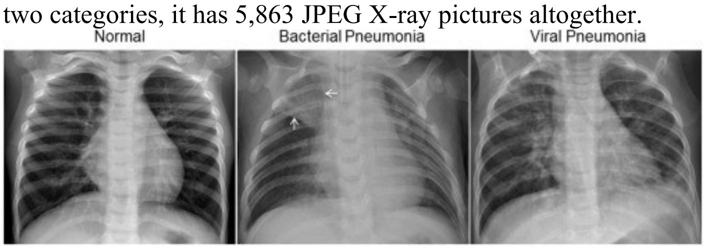

Figure II.1 Dataset Sample

C. Steps

- Preparation of the dataset: Low-quality or unreadable scans were eliminated during quality inspection of the chest X-ray pictures. Accuracy was ensured by expert physicians grading the diagnosis.
- Choice of Models: For the extraction of pertinent features, transfer learning techniques (VGG16, MobileNet V2) were used to leverage pre-trained models on big datasets. Furthermore, a CNN architecture was used because of its capacity to acquire knowledge from graphic representations of images.
- Training of Models: To understand the links between X-ray pictures and their associated categories (Normal/Pneumonia), the models underwent training using the previously assembled dataset (train set).
- Evaluation of Models: To examine the performance of the trained models, they were tested on the validation set. To guarantee that the labels were accurate, the assessment set was verified by experts who provided the dataset.
- Prediction Study: In order to assess the models' performance and capacity for interpretation, they were lastly evaluated using a test set designed to predict health conditions (Pneumonia/Normal) in images that had not yet been observed.

D. Transfer Learning Approach

This algorithm followed an already established (Fchollet, n.d.) workflow consisting of four main stages and one optional stage.

- Layers from a previously learned model are employed. This entails reusing pre-existing layers from a model that was trained on a big dataset, often in a comparable domain or on a similar job. It is done to make use of the encoded learned representations, features, and patterns in these layers. By using these learnt characteristics, the model gets off to a good start, potentially improving its ability to perform on a fresh dataset.
- Freeze them to prevent subsequent training cycles from deleting any of the information they contain. This involves securing the weights of the pre-trained layers so that they remain constant throughout training cycles. Freezing prevents these layers from being changed or updated throughout the fresh dataset training procedure.
- On top of the frozen layers, add some additional trainable layers. They'll figure out how to transform previous characteristics into predictions on a fresh dataset. The additional trainable layers allow the model to be fine-tuned to the peculiarities of the fresh data set. They learn to identify higher-level characteristics and patterns associated with the activity in question while relying on the basic information provided by the pre-trained layers.
- On the given dataset, train the new layers. In order to minimise the discrepancy between the predicted and actual labels, this requires showing the newly added trainable layers to the new dataset and modifying their parameters during training iterations (epochs). This procedure supports the model's learning of the distinct characteristics and patterns seen in the new dataset. By training, the model expands on the information from the previously learned layers and refines its parameters to produce precise predictions that are unique to the current dataset.
- Fine-tuning refers to retraining a pre-trained model on a new dataset at a much lower learning rate by unfreezing any or all of its layers. Fine-tuning tries to further adjust the entire model or specific sections of it to the new data by enabling previously frozen layers to update their weights. This is done after placing trainable layers over the previously frozen pre-trained layers and training them on the fresh set of data. This process involves gradually modifying the features that were learnt from the pre-trained model in order to better match the unique attributes of the fresh dataset. It facilitates the model's ability to recognise more complex patterns and correctly adjust to the peculiarities of the fresh input.

E. CNN Approach

The Convolutional Neural Network followed a very simple approach of simply setting up the network, training and evaluating it.

The convolutional, pooling, and fully connected layers of the network's architecture (Figure II.2) have been constructed to analyse input and extract pertinent information.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 62, 62, 32)	896
max_pooling2d (MaxPooling2D)	(None, 31, 31, 32)	0
conv2d_1 (Conv2D)	(None, 29, 29, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 32)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 128)	802944
dense_1 (Dense)	(None, 1)	129

Figure II.2 CNN Model Summary

Conv2D layers to extract features. MaxPooling2D layers to reduce dimensions by downsampling data. Flatten layers to convert data into a one-dimensional array. Dense layers for pattern recognition that are completely unified.

F. Distinction in Approach

The unique aspect of this research is how it predicts medical conditions from chest X-ray pictures using deep learning techniques, namely transfer learning using VGG16 and MobileNet V2 combined with a Convolutional Neural Network. The Guangzhou Women and Children's Medical Centre provided the dataset, which was subjected to rigorous quality checks and diagnosis verification by specially trained medical professionals. The models ensured a strong foundation for learning by utilising pre-trained networks to retrieve pertinent information through the application of transfer learning. The CNN significantly improved the model's capabilities with its straightforward configuration, which included Dense layers for pattern recognition, MaxPooling2D for dimension reduction, Flatten for data conversion, and Conv2D for feature extraction. This method has special merit as it uses pre-trained models for transfer learning in medical image analysis, which is supported by stringent dataset quality control and professional validation.

III. Results

A. Model Summary

1) Transfer Learning Architecture

The architecture of the two transfer learning algorithms is identical, as an instance the MobileNetV2 architecture is described and illustrated. It begins with an input layer ('input_2') that handles photos with dimensions of 160x160 and three colour channels. A sequential layer for data augmentation ('sequential') is included in the model, which performs operations such as random flips and rotations. Then, two lambda layers ('tf.math.truediv' and 'tf.math.subtract') execute pixel value rescaling to prepare the input data for the MobileNetV2 model. The MobileNetV2 functional layer ('mobilenetv2_1.00_160') is at the heart of the model, extracting characteristics from photos to produce an output shape of (None, 5, 5, 1280). The spatial dimensions are then reduced via a global average pooling layer ('global_average_pooling2d') to generate a shape tensor (None, 1280). Finally, a dropout layer (dropout) with a rate of 0.2 is used for regularisation, guaranteeing that 20% of the elements in the preceding layer are randomly set to zero during training to prevent overfitting (Figure III.1).

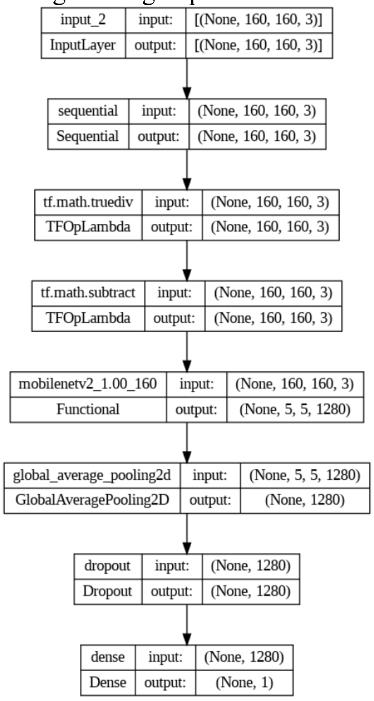

Figure III.1 Transfer Learning Architecture

2) CNN Architecture

The CNN model (Figure III.2) includes an input layer for 64x64 RGB pictures. It starts with a convolutional layer that applies 32 3x3 filters with ReLU activation, yielding 32 62x62 feature maps, then max pooling with a 2x2 window and downsampling to 31x31. After that, another convolutional layer applies 32 3x3 filters, resulting in 32 feature maps of size 29x29, which are then max pooled to 14x14. For fully connected layers, the next flattening layer converts the data into a 1D array of length 6272. The first dense layer is made up of 128 neurons that are activated by ReLU, ending in an output layer that uses a sigmoid function for binary classification. The model has 813,217 trainable parameters spread throughout its layers.

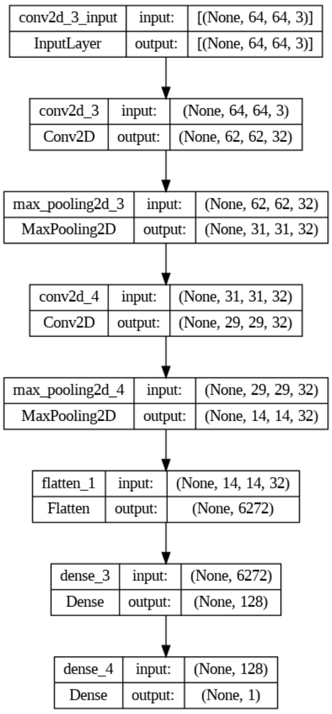

Figure III.2 Deep Neural Network Architecture

The given confusion matrix (Figure III.3) depicts the model's performance on a test dataset, with a 2x2 matrix structure. In particular, the model successfully identified examples belonging to the negative class (class 0) with 234 true negatives (TN) but failed to identify instances belonging to the positive class (class 1) with 390 false negatives (FN). Notably, no false positives (FP) or true positives (TP) were reported. This indicates a major problem with the model's ability to properly identify positive class instances, which might indicate a class imbalance, architectural flaws, or a need for more refining to improve the model's performance on positive class predictions.

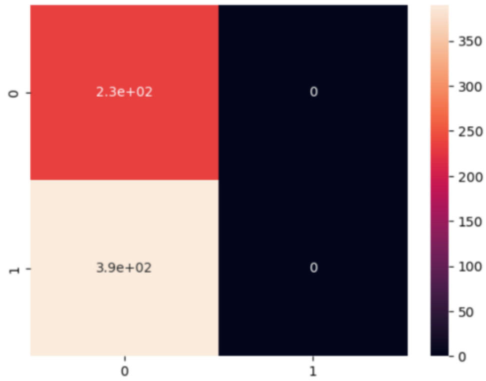

Figure III.3 CNN Confusion Matrix

B. *Results of the Models*

During feature extraction, MobilenetV2 showcased good performance on the validation set. It achieved approximately 96% accuracy on the validation set within 10 epochs. However, the learning curves indicated a trend of improving accuracy and decreasing loss yet revealed signs of overfitting due to the discrepancies between training and validation metrics. Upon fine-tuning, the MobilenetV2 model reached nearly 98% accuracy on the validation dataset, as shown in Figure III.4.

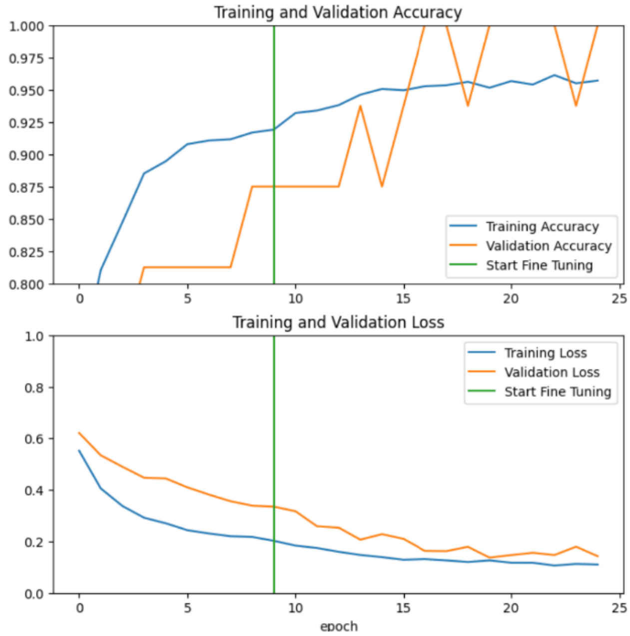

Figure III.4 MobileNetV2 Results

Applying frozen base layers for initial training, the transfer method of learning with VGG16 produced a 74% accuracy on the training set and a stationary 50% accuracy across 10 epochs on the validation set. Following 14 more epochs of unfreezing some layers for fine-tuning, the accuracy only slightly improved, averaging between 74 and 75 per cent on the training set and a steady 50 per cent on validation. The constant validation accuracy suggests that, despite the model's efforts to be fine-tuned, it was unable to learn from the available data and struggled with generalization (Figure III.5).

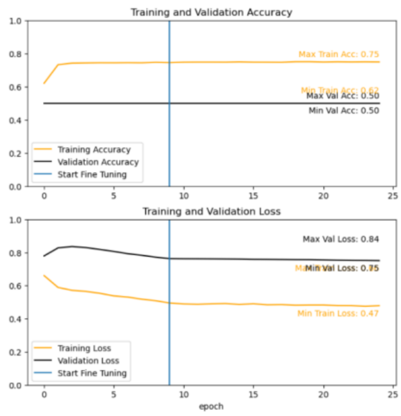

Figure III.5 VGG16 Results

The CNN model's (Figure III.6) training across ten epochs shows variability in both accuracy and loss. The first epoch has a maximum accuracy of 93.75% on the validation set, and an accuracy of 82.25% on the training set, with a training loss of 0.4061 and a validation loss of 0.3484. Yet, the outcomes of the successive epochs differ. On the training set, the accuracy stabilizes at 92-94%, while on the validation set, it varies significantly, reaching levels as low as 62.5% in later epochs. Similarly, the validation loss varies, with the lowest being 0.2609 during the fifth epoch and the largest being 1.1640 during the last epoch.

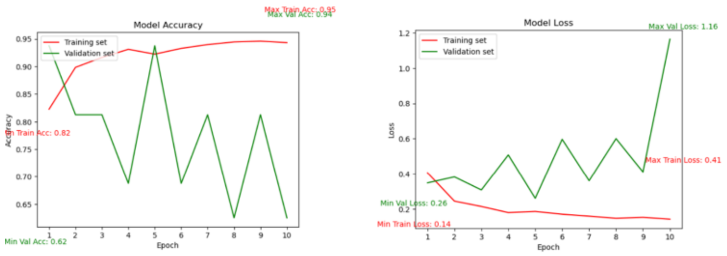

Figure III.6 CNN Results

The evaluation revealed the models' capacity to predict pneumonia and normal instances accurately. These AI-based models offered a potential solution to improve diagnostic accuracy, reduce human error, and provide more precise diagnoses for pneumonia from X-ray images.

IV. Comparison Study

A. *Algorithm Comparison*

Both VGG16 and MobileNetV2 models, used for transfer learning, exhibited promising results. VGG16, known for its deep representation and computational complexity, displayed strong capabilities in extracting features from the chest X-ray images. In contrast, MobileNetV2, optimized for efficiency and speed, demonstrated promising outcomes, particularly suitable for applications with limited resources or mobile platforms. Additionally, the CNN model, employed as part of the study, proved effective in analyzing and understanding the images. It showed its ability to handle complex medical image data efficiently. Discussion and Future Work.

1) *Transfer Learning Approach*

The study adopted a well-established transfer learning strategy, incorporating pre-trained VGG16 and MobileNetV2 models. These models, designed on large datasets, were repurposed to learn from the medical image dataset, leveraging their encoded representations and patterns to kickstart the learning process. The subsequent fine-tuning of these models further refined their ability to recognize unique patterns present in the new dataset.

a) Strengths

- VGG16 excels in feature extraction and is exceptionally good at pulling out detailed features from images but demands higher computational resources.
- On the other hand, MobilenetV2, optimized for efficiency, delivers notable performance while being resource-friendly.

b) Limitations

- Despite its efficiency in learning representations, these models might face challenges with smaller, domain-specific datasets.
- Fine-tuning enhances their ability to recognize unique patterns, yet they might exhibit signs of overfitting due to discrepancies in dataset sizes and specificity.

2) *CNN Approach*

The CNN architecture was implemented, focusing on feature extraction, dimension reduction, data conversion, and pattern recognition. This approach allowed the model to learn distinct characteristics from the chest X-ray images, ultimately contributing to accurate predictions.

a) Strengths

- CNN can handle spatial hierarchies with the images, capturing complex patterns and relationships between pixels effectively.
- It does not rely on pre-trained weights, which allows for more specialized learning and adaptation to the dataset at hand.

b) Limitations

- CNN may require more extensive training and larger datasets to grasp complex patterns effectively.
- Without leveraging pre-trained features, they might need more data to achieve comparable performance to transfer learning models.

B. *Comparison Of Models Per Algorithm*

1) *CNN: Model 1 vs Model 2*

Model 1 (Figure III.6) has a simpler architecture, with two convolutional layers of 32 filters each, followed by a dense layer of 128 neurons, obtaining a maximum validation accuracy of 93.75% and a minimum loss of 0.2831. Its training is more efficient, implying faster learning. Model 2 (Figure IV.1), on the other hand, has a more complex architecture with three convolutional layers (64, 64, 128 filters), two dense layers (256 and 128 neurons), and a maximum validation accuracy of 81.25% and a minimum loss of 0.3777. Model 2's training, on the other hand, exhibits higher fluctuations, indicating probable overfitting or complexity that does not efficiently capture patterns.

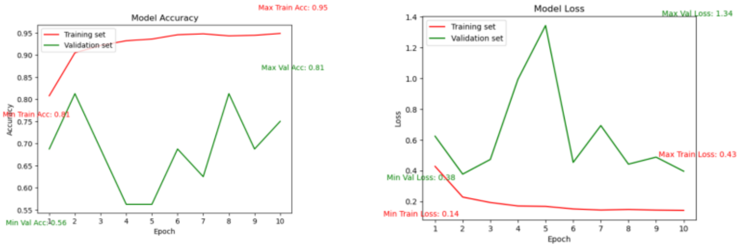

Figure IV.1 CNN Model 2

2) VGG16: Model 1 vs Model 2

Both Model 1 (Figure III.6) and Model 2 (Figure IV.2) utilize transfer learning from VGG16 with additional layers, yet both struggle with poor performance and an inability to generalize beyond random guessing, maintaining consistent accuracy around 74-75% and validation accuracy at a mere 50%. Model 1 employs global average pooling, dropout, and a final dense layer with 1 neuron, while Model 2 includes additional dense and dropout layers. Despite these architectural variances, both models display consistent loss values (around 0.48-0.49 for Model 1 and 0.20 for Model 2) throughout training, signifying a failure to learn meaningful patterns from the data. These models showcase a shared issue—incapable of learning and generalizing effectively, potentially indicating problems with the data, preprocessing, or the complexity of the models preventing them from capturing relevant features.

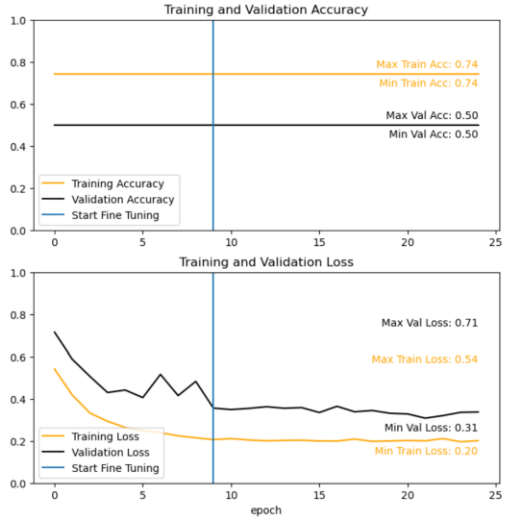

Figure IV.2 VGG Model 2

3) MobileNetV2: Model 1 vs Model 2

Model 1 (Figure III.4) is composed of data augmentation, preprocessing, a base model, global average pooling, a dropout layer, and a prediction layer. Its performance showcases consistent high accuracy, reaching around 95-96% on the training set by the final epoch (Epoch 24/24), with validation accuracy ranging between 87-100%, highlighting its strong generalization capability. In contrast, Model 2 (Figure IV.3) includes data augmentation, preprocessing, a base model, global average pooling, a flatten layer, dense layers, dropout layers, and a prediction layer. However, it struggles to learn effectively, stagnating at approximately 74-75% accuracy on both training and validation sets across Epochs 10 to 24. Validation accuracy remains consistently below 50%, indicating an inability to generalize well and significantly underperforming compared to Model 1.

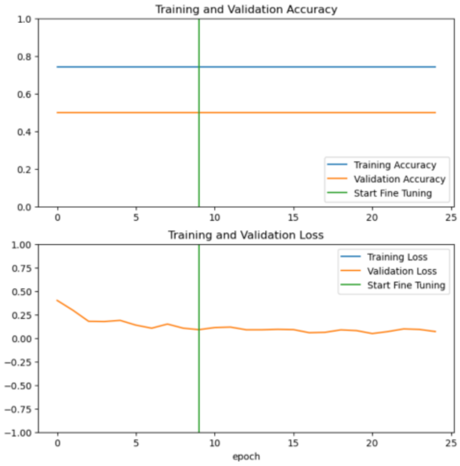

Figure IV.3 MobileNetV2 Model 2

V. DISCUSSION

The study identifies major variances in performance amongst the models used. MobileNetV2 (Model 1) demonstrated robust generalization and consistently high accuracy, showcasing its potential for effective pneumonia diagnosis from X-ray images. Conversely, the CNN architecture (Model 1) displayed promising initial performance but struggled with fluctuations during training, potentially indicating overfitting or insufficient pattern capture. Moreover, VGG16-based models, both Model 1 and Model 2, consistently exhibited poor performance, barely surpassing random guessing, highlighting a significant challenge in learning meaningful patterns from the provided dataset. These findings emphasise the importance of architectural complexity and training strategies in model performance, emphasising the need for delicate changes in architecture design and training methodologies to improve the models' ability to accurately diagnose pneumonia from X-ray images.

VI. FUTURE WORK

- Enhancing Model Adaptability: To improve the accuracy and reliability of deep learning models used for pneumonia detection, it is essential to evaluate their performance across various demographic subgroups (e.g., different ages, and genders), as well as under varying image quality conditions. By understanding how these models hold up against different scenarios, we can better understand their limitations and potential biases, ultimately leading to stronger model adaptations that are better suited for real-world use cases. For instance, a model that performs poorly among children may need additional training data specifically tailored to pediatric patients to ensure optimal performance. Similarly, a model that struggles with low-quality X-ray images may require adjustments to its architecture or training protocols to account for degraded image acquisition processes commonly encountered in resource-constrained settings.

- Broadening Applications: The wider applicability of deep learning models in medicine depends critically upon addressing the challenges associated with obtaining large, high-quality datasets representative of diverse patient populations. Once this challenge has been overcome, there exists significant potential for expansion into other medical imaging areas, including but not limited to cardiovascular disease, neurology, and musculoskeletal disorders. Furthermore, exploring hybrid approaches integrating deep learning with traditional computer vision methods might help fill any remaining gaps in performance, ensuring seamless integration between AI and human expertise in medical decision-making. The advent of user-friendly, cloud-based platforms offering easy accessibility to cutting-edge computational resources will also aid in accelerating advancements in this field.
- Refining Model Performance: Future research should aim to refine the fine-tuning process to enhance the capability of deep learning models in identifying subtle patterns indicative of pneumonia. This may involve incorporating larger, more comprehensive annotations from diverse populations to bolster the model's generalization abilities. Additionally, investigating techniques such as transfer learning, where pre-trained models are adapted for specific tasks through adjustments to their weights or architecture, could lead to improved adaptation and reduced overfitting. Another promising approach involves using multi-modal imaging inputs, combining X-ray findings with other diagnostic modalities, such as CT scans or MRI exams, to augment feature extraction and increase overall diagnostic accuracy.

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