Analysis Towards Classification of Infection of Pneumonia from Chest X-Ray Images of Pediatric Patients Using Deep Learning Algorithms

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***Abstract*—Pneumonia is a common respiratory infection that can lead to severe health complications if not detected and treated promptly. In recent years, deep learning models have emerged as powerful tools for medical image analysis, including the detection of pneumonia from chest scans. This research focuses on exploring the effectiveness of deep learning models in pneumonia detection and their potential implications for clinical practice.**

The research involved the utilization of medium dataset of chest scan images, with 2213 for training, from which we have 554 normal images and 1659 pneumonia images, 418 validation from which we have 63 normal images and 355 pneumonia images, and 421 for testing. The ground truth labels are two classes, pneumonia and normal, pre-trained models like ResNet152, ResNet101, AlexNet and a self-build architecture that was named AnotiNet was employed to extract meaningful features from the scans and learn complex patterns associated with pneumonia.

The model was trained using appropriate optimization techniques, loss functions, and evaluation metrics. The training process aimed to fine-tune the deep learning model on the pneumonia dataset, enabling it to accurately classify chest scans as either pneumonia or normal. Extensive validation and testing were conducted to assess the model's performance and evaluate its ability to generalize to unseen data. From this research, it is found that all the models had a significantly high accuracy score.

***Index Terms*—Deep Learning, ResNet152, ResNet101, AlexNet, AnotiNet, Pneumonia.**

I. Introduction

Pneumonia is a common and serious respiratory infection characterized by inflammation of the air sacs in one or both lungs. It poses a significant burden on healthcare systems worldwide, with approximately 1.3 million adults requiring hospitalization for community-acquired pneumonia in the United States alone each year [1]. Pneumonia can be caused by various pathogens, including bacteria, viruses, and fungi, with viral pneumonia accounting for a substantial proportion of cases [2]. Detecting pneumonia accurately and efficiently is crucial for timely diagnosis and appropriate treatment. This is particularly relevant in the context of co-infections, such as the recent COVID-19 pandemic, where prompt identification of pneumonia can aid in patient management and infection control. [3]. Traditional diagnostic methods for pneumonia include clinical assessment, laboratory tests, and imaging techniques such as chest X-rays, which can reveal characteristic opacities in the lungs [4].

However, the advent of deep learning models has revolutionized the field of medical image analysis, offering new opportunities for automated pneumonia detection. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated remarkable performance in various medical imaging tasks, including pneumonia detection [1]. These models can learn intricate patterns and features from large-scale datasets, enabling accurate and efficient analysis of chest scans for pneumonia [2]. By leveraging the power of deep learning, researchers and clinicians can potentially enhance the speed and accuracy of pneumonia diagnosis, leading to more timely interventions and improved patient outcomes. Moreover, the application of deep learning models in pneumonia detection has the potential to assist healthcare professionals in resource-limited settings, where access to specialized expertise and imaging facilities may be limited [3].

In this study, we aim to develop and evaluate a deep learning model for pneumonia detection in chest scans. By training the model on a large dataset of annotated chest images, we expect it to learn discriminative features indicative of pneumonia. The performance of the model will be assessed using various evaluation metrics, such as accuracy, precision, recall, confusion matrix and area under the receiver operating characteristic curve (AUC-ROC). The ultimate goal is to provide a reliable and efficient tool for pneumonia detection, complementing existing diagnostic approaches and improving patient care.

A. Datasets

Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou. All chest X-ray imaging was performed as part of patients' routine clinical care. For the analysis of chest x-ray images, all chest radiographs were initially screened for quality control by removing all low quality or unreadable scans. The dataset which is available to download was gotten from mendeley [5]. The dataset is organized into 2 folders (train and test) and contains subfolders for each image category (Pneumonia/Normal). There are 2,631 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal). The dataset was later splitted into 4 folders, train, test, valid and train valid, train valid is the combination of all the pneumonia images in one

TABLE I

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Number of Images in folder				
Image Category	Train	Test	Valid	Train Valid
Pneumonia	1659	421	418	2014
Normal	554		63	617

folder and same for normal images. The numbers of the images are shown in table I.

Figures 1 show some sample of the images, pneumonia labeled as (a), and normal labeled as (b).

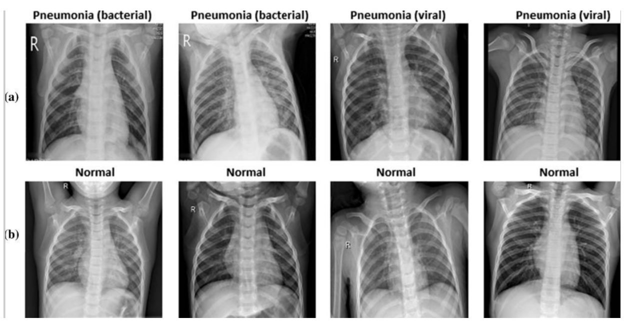

Fig. 1. Sample of Chest X-Ray Images with Pneumonia and Normal

II. RELATED WORK

A. Background

According to the World Health Organization (WHO), pneumonia is responsible for millions of deaths worldwide, particularly among children under the age of five and older adults [6] [7]. Detecting pneumonia from chest X-ray images of patients has been a significant challenge, primarily due to the scarcity of available data [8]. Various machine learning techniques have been explored to address this problem, but they often require manual feature selection or extraction, which can be time-consuming and may not capture all relevant information in the dataset [9]. In contrast, deep learning models have the ability to automatically extract features from the data, making them well-suited for image classification and segmentation tasks [10] [11]. Convolutional neural networks (CNNs) have emerged as powerful deep learning models for image classification tasks and have gained significant popularity among researchers [12]. CNNs leverage the convolutional operations to extract essential features by convolving input images with filters. This enables them to learn discriminative patterns and achieve superior performance compared to traditional machine learning algorithms or traditional image processing methods in image classification tasks [8]. In this project, a deep learning approach using different CNN-based architecture is employed to classify chest X-ray images and detect pneumonia although a self-architecture(Sequential) was also tried. To ensure the effectiveness of the models, it is important to compare it with established architectures. Therefore, transfer learning is utilized, which involves leveraging pre-trained models to make predictions on the current task [13]. Transfer learning offers several advantages, including saving computational resources and avoiding the need to train a deep neural network from scratch. It is particularly useful in biomedical imaging, where data scarcity often poses a challenge. By transferring knowledge from larger datasets, transfer learning can enhance classification performance on smaller datasets.

By combining the automatic feature extraction capabilities of CNNs and the benefits of transfer learning, this project aims to develop an accurate and efficient model for pneumonia detection from chest X-ray images. The proposed model has the potential to improve diagnostic capabilities and efficiency in pneumonia detection, leading to enhanced patient care and outcomes.

B. Review of Related Work

Several studies have been conducted in the field of pneumonia detection from chest X-ray images using deep learning techniques. These studies have explored various methodologies, datasets, and model architectures to improve the accuracy and reliability of pneumonia diagnosis. [14] introduced CheXNet, a deep learning model based on convolutional neural networks (CNNs), achieving radiologist-level accuracy in pneumonia detection. [15] proposed a two-stage framework that utilized a CNN to identify potential regions of interest (ROIs) in chest X-ray images, followed by a multi-scale CNN for pneumonia classification, resulting in improved accuracy compared to traditional methods. [16] incorporated a self-attention mechanism into their deep learning model, allowing the model to focus on informative regions and improving pneumonia detection accuracy. [17] combine five state of the art pre-trained Deep Learning models namely VGG16, Xception, InceptionV3, ResNet50 and DenseNet201 for the diagnosis of pneumonia from a number of pediatric patients. For the study the researchers trained their proposed model on a dataset containing more than 5800 X-Ray images of children aged between 1 to 5. The proposed model achieved an accuracy score of 97.3% with values of precision, recall, recall, and f1-scores of 97.5%, 98% and 97.8%.

Transfer learning has also been explored for pneumonia detection. [18] fine-tuned pre-trained CNN models, such as VGGNet and ResNet, on a smaller dataset of pneumonia cases, demonstrating the effectiveness of transfer learning even with limited data. [19] investigated an ensemble approach that combined predictions from multiple deep learning models, including DenseNet, InceptionNet, and ResNet, resulting in enhanced accuracy and robustness in pneumonia classification. [20] used CNN, ResNet18, AlexNet, DenseNet201 and SqueezeNet to detect bacterial and viral Pneumonia from X-Ray images. Three schemes of classification were reported by the authors in the study: normal vs. pneumonia, bacterial vs. viral pneumonia, and normal, bacterial, and viral pneumonia and the accuracy scores of each of the schemes were 98%, 95%, and 93.3%, respectively.

Other studies have focused on data augmentation techniques. [21] explored the use of generative adversarial networks (GANs) to generate synthetic chest X-ray images, augmenting the training data and improving the performance of pneumonia detection models. [22] employed a mixup strategy, combining pairs of chest X-ray images and their corresponding labels, to generate augmented samples for training deep learning models, achieving improved performance in pneumonia detection.

In addition to CNN-based approaches, alternative deep learning architectures have been investigated. [23] proposed a deep belief network (DBN) for pneumonia detection, leveraging its ability to learn complex representations and achieve high accuracy in pneumonia classification.

Furthermore, studies have explored the application of explainable AI in pneumonia detection. [24] developed a hybrid deep learning model that combined CNNs with a gradient-weighted class activation mapping (Grad-CAM) method, enabling visual interpretability and aiding in identifying regions of interest for pneumonia detection .

These studies collectively demonstrate the effectiveness of deep learning techniques, including CNNs, transfer learning, attention mechanisms, data augmentation, and alternative model architectures, in improving pneumonia detection accuracy from chest X-ray images.

III. Experiments

A. Performance Metrics

In evaluating the performance of the classification model on imbalanced data, We carefully selected performance metrics that take into account the unequal distribution of classes. Given the significant class imbalance with 2014 instances of pneumonia and 617 instances of normal, it is crucial to assess the model's effectiveness accurately. To address this, We have chosen metrics such as the F1-Score, micro-average F1-Score, and area under the Receiver Operating Characteristics Curve (AUC). These metrics consider both precision and recall, which are essential for correctly identifying positive instances while minimizing false positives. Additionally, We have included the macro-average of precision, recall, F1-Score, and AUC to provide a comprehensive assessment of the model's overall performance across classes. By incorporating these metrics, We accurately evaluate the model's ability to handle class imbalance and make informed decisions about its effectiveness in classifying pneumonia and normal cases.

B. Deep Learning Algorithms Used for this Project

In this project three different pre-trained models and one self-built architecture(AnotiNet) have been implemented to reach the research aim. The models are ResNet152, ResNet101 and AlexNet.

1) ResNet152: ResNet152 is a deep convolutional neural network architecture that belongs to the ResNet (Residual Network) family. It is a powerful and widely used model in computer vision tasks, particularly in image classification and feature extraction.

The ”152” in ResNet152 refers to the number of layers in the network, making it a very deep model. ResNet152 introduces the concept of residual connections or skip connections, which address the problem of vanishing gradients in deep networks. These connections allow information from earlier layers to bypass several layers and directly reach deeper layers, facilitating the flow of gradients during training and enabling the network to learn more effectively.

ResNet152 is pretrained on large-scale image datasets, such as ImageNet, which helps it capture general image representations and extract meaningful features. The architecture consists of repeated building blocks, known as residual blocks, containing convolutional layers, batch normalization, and non-linear activation functions, such as ReLU (Rectified Linear Unit). The use of residual blocks enables ResNet152 to learn complex patterns and capture high-level features in images.

With its deep architecture and skip connections, ResNet152 has achieved state-of-the-art performance on various image classification challenges, demonstrating its ability to learn intricate representations and handle complex visual tasks. It has become a popular choice for many computer vision applications, including object recognition, image segmentation, and transfer learning, due to its excellent performance and robustness. Figure 2 shows ResNet152 architecture.

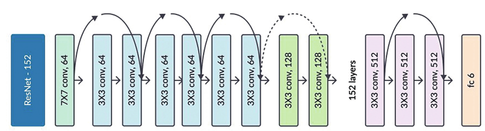

Fig. 2. ResNet152 CNN architecture layers [25]

2) ResNet101: ResNet101 is a deep convolutional neural network architecture introduced by [26] ResNet101 is an extension of the original ResNet architecture, featuring 101 layers. The key innovation of ResNet101 is the introduction of residual blocks, which allow for the training of very deep networks by addressing the degradation problem encountered in deeper architectures. These residual blocks utilize skip connections to directly connect earlier layers to later layers, allowing the network to learn residual mappings instead of trying to learn the entire mapping from scratch.Figure 3 shows ResNet101 architecture.

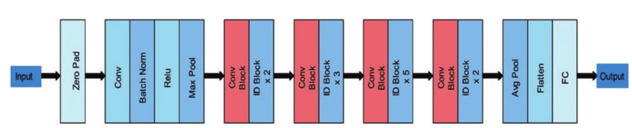

Fig. 3. ResNet101 CNN architecture layers [27]

3) AlexNet: AlexNet is a deep convolutional neural network architecture proposed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton [28] It was designed specifically for large-scale image classification tasks.

AlexNet was a breakthrough model that won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012, significantly advancing the field of deep learning. It consists of eight layers, including five convolutional layers and three fully connected layers.

One of the key contributions of AlexNet is the use of rectified linear units (ReLU) as activation functions, which helped alleviate the vanishing gradient problem and accelerate training. It also introduced the concept of using dropout regularization to reduce overfitting during training.

AlexNet demonstrated the potential of deep convolutional neural networks in achieving superior performance on challenging visual recognition tasks. Its architectural principles, such as convolutional layers, ReLU activations, and dropout regularization, have since become foundational elements in many modern deep learning models.Figure 4 shows AlexNet architecture.

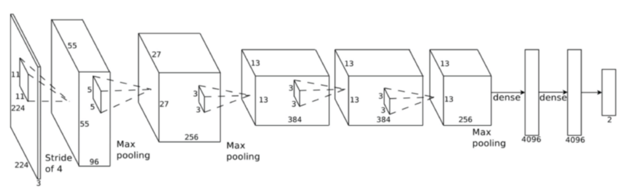

Fig. 4. AlexNet CNN architecture layers [29]

4) Self Architecture(AnotiNet): Building a custom sequential architecture allows for the creation of a neural network tailored to specific tasks and datasets. By defining the architecture layer by layer, it provides flexibility and control over the model's structure and functionality. The process of building a sequential architecture involves determining the number and type of layers to include, in this research we stopped at second layer, We can further research more layers to see if there will be improvement in our model.

It also gives us the ability to set the appropriate activation functions, configure the input and output dimensions, and specify any additional operations like pooling or regularization. Iterative experimentation and fine-tuning was done to achieve optimal performance though due to computational time we could not beat the base model of ResNet152 but we achieved a tangible progress during the process. Building a custom sequential architecture allows us to customize , enabling the creation of models that are specifically tailored to the problem at hand. It provides the flexibility to experiment with different architectural choices and empowers us to explore innovative solutions. Table II shows the Layer's name, shape, and parameter values for our self built architecture.

IV. METHODOLOGY

For this research, The initial step involved loading the data from various folders and storing it in cloud storage

TABLE II

LAYER'S NAME, SHAPE, AND PARAMETER VALUES IN CUSTOM CNN

Layer	Output Shape	Parameters
conv1.weight	(32, 3, 3, 3)	864
conv1.bias	(32,)	32
batch1.weight	(32,)	32
batch1.bias	(32,)	32
conv2.weight	(64, 32, 3, 3)	18432
conv2.bias	(64,)	64
batch2.weight	(64,)	64
batch2.bias	(64,)	64
fc1.weight	(30, 12544)	376320
fc1.bias	(30,)	30
fc2.weight	(2, 30)	60
fc2.bias	(2,)	2
Total Parameters		**395106**

for data analysis. Subsequently, the dataset was divided into training, testing, validation and train validation sets, followed by augmentation to enhance the models' training process and finally the model performances are evaluated using several metrics as stated in Performance metrics above. The code used in this experiment can as well be viewed here.

1) Data Preparation: The sizes of the images are varying from 1750 pixels to 2000 pixels, It was further reduced to 120 pixels to 120 pixels and seen in figure 5. In this experiment, the cell images are further scaled to 64 pixels in height and 64 pixels in width. Dataset splitting is the general part of model building. The amount of the data impacts how the dataset is split. In this research, the dataset is split into 60% of the training set, 20% of the validation set, and 20% of the testing set using split folders library, The model is trained to find patterns in the data by utilizing the training set. The validation set is used to test the model's performance during training. Finally, the model is tested with a test set when it has completed training.

Fig. 5. Resized Image

2) Parameters: The experiment has been carried out several times with a number of different parameters as seen on table III and the ones with the best results obtained have been used for the final results. Throughout the studied literature the researcher has used the Adam optimiser which is the best optimiser , A test was carried out on ResNet152 to determine if Adam is the best optimizer as shown in table IV, Though SDG has a Lower Val Loss of 0.089 while Adams has 0.092 but it took it 40 epoch to achieved that while Adams took just 13. This makes Adams the best fit for this research.

Also since this is a binary classification we employ cross-entropy loss function . The convolution and hidden layers are activated using the "Softmax" Learning Rate 0.0001 was used all through, an experiment was also carried out on ResNet152 to determine if this is the best learning rate as seen in table V as it has the lowest valid loss of 0.37671 compared to the other learning rate.

TABLE III
GENERAL HYPERPARAMETERS USED

Parameter Name	Type/Value
Batch Size	32
Epochs	50
Dropout	0.2
Activation Function	Softmax
Optimizer	Adam
Learning Rate	1e-3 (FOUND_LR)
Loss Function	CrossEntropyLoss

TABLE IV
COMPARISON OF OPTIMIZERS

Optimizer	Stopped epoch	Best Val Loss	Best Val Accuracy
SGD	40	**0.089**	97.36
Adamax	14	0.103	97.36
Adams	13	0.092	96.88

TABLE V
COMPARISON OF LEARNING RATE

Learning Rate	Stopped epoch	Best Valid Loss
0.01	12	0.42855
0.001	23	0.37682
0.0001	15	**0.37671**

V. RESULTS AND DISCUSSION

After training our models, we generated two plots for each model, each having training and validation losses plot and training and validation accuracies. It is important to analyze the overall trend rather than focusing solely on individual fluctuations. A gradual decrease in both the training and validation losses indicates that the model effectively learns and minimizes the loss function throughout the training process. This decreasing trend suggests that the model fits the training data well and generalizes to the validation data. Additionally, a gradual increase in both the training and validation accuracies indicates that the model's performance improves and becomes more accurate as the training progresses. The high training accuracy signifies that the model has learned to classify the training data correctly, while the relatively high validation accuracy suggests that the model generalizes well to unseen validation data. Figure 6, 7, 8 and 9 shows the four model and their behaviour during training.

From Figure 6 it is seen that the Algorithm ran a total of 16 epoch before it stops, It is observed that the model performed well overall, as the training loss is lower than validation loss and the training accuracy also higher than the validation accuracy.

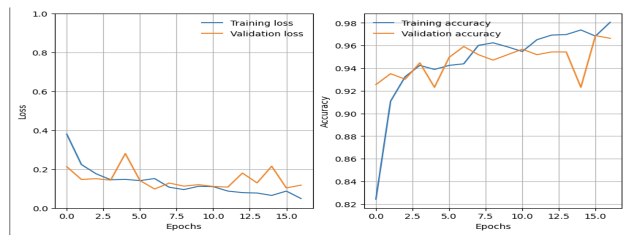

Fig. 6. Performance of ResNet152 During Training

From Figure 7 it is seen that the Algorithm ran a total of 28 epoch before it stops, Though there is a sharp decline for validation accuracy at epoch 6, This can be overlooked as we have to analyze the overall trend rather than focusing solely on individual fluctuations It is observed that the model performed well.

Fig. 7. Performance ResNet101 During Training

According for Figure 8, AlexNet has similar observation with the other with respect to decrease in loss but failed to perform well for accuracy as the validation accuracy is higher that the train accuracy, The model ran a total of 27 times to reach the desired validation loss with the best weights.

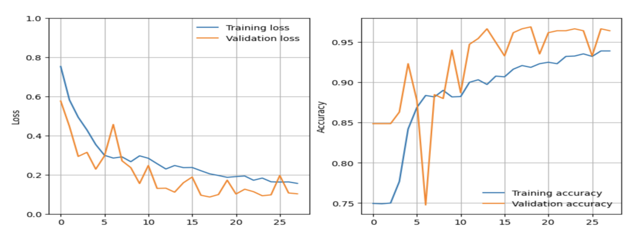

Fig. 8. Performance AlexNet During Training

According to Figure 9 which is the self built Architecture, It also followed same pattern as Alexnet, it also ran 27 times to reach the desired validation loss with the best weights.

TABLE VI
A COMPARISON OF THE OVERALL PERFORMANCE THE MODELS RESULTS REPORTED ON THEIR BEST EPOCH.

Method	Epoch		Per class Recall		micro-average		macro-average			
	Early Stop	Best epoch	Normal	Pneumonia	F1	AUC	Precision	Recall	F1	AUC
Resnet152	16	16	0.76	0.98	0.95	0.97	0.92	0.87	0.89	0.97
Resnet101	28	19	**0.81**	**0.99**	**0.96**	0.97	**0.94**	**0.90**	**0.92**	**0.98**
AlexNet	27	25	0.76	0.98	0.94	0.97	0.91	0.89	0.90	0.97
AnotiNet	27	23	0.76	0.98	0.95	0.97	0.92	0.87	0.89	0.97

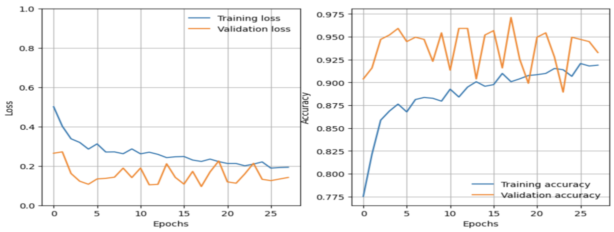

Fig. 9. Performance AnotiNet During Training

We conducted a performance comparison of the models and found that ResNet101 outperformed the other three models, achieving a macro-average F1-Score of 0.92 and an AUC of 0.98, as shown in Table VI. All models achieved an accuracy score of over 90%, and their high AUC values indicate that they have effectively learned from the data.

However, it is important to note that accuracy alone does not provide a complete assessment of classifier performance. Therefore, we have employed other metrics to comprehensively analyze the models' performance.

Additionally, by examining the table VI and further validating with the Confusion Matrices in Figure 10 , we observed that the ResNet101 model demonstrates a higher accuracy (81%) in predicting Normal patients compared to the other models. This aspect holds significance in healthcare industries as misclassification of patients can lead to improper treatment. Consequently, ResNet101 emerges as the preferred model for this experiment due to its superior ability to predict a higher number of Normal patients among the trained models.

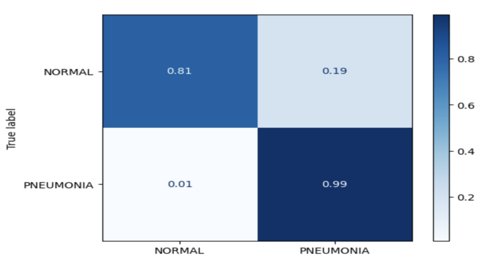

Fig. 10. Confusion Matrix of the Predictions made by RexNet101

A. Research Limitations

A limitation of this project was the reliance on Google Colab for running the experiments. Google Colab provides limited access to GPUs, and there were instances where the runtime would expire or disconnect due to resource limitations.

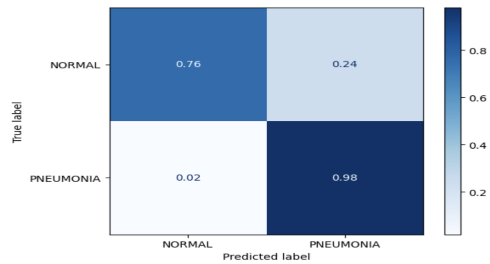

Fig. 11. Confusion Matrix of the Predictions made by RexNet152

This resulted in interruptions and delays during the training and evaluation processes. Additionally, in order to ensure consistent access to GPU resources, a paid subscription was required. As a result, the cost of running the experiments on Google Colab had to be taken into consideration. These limitations impacted the efficiency and scalability of the project, as it relied on external resources that were not always readily available or cost-effective.

VI. CONCLUSION

In conclusion, this project successfully addressed the task at hand and achieved promising results. ResNet101 emerges as the preferred model for this experiment as it has the highest value for all the metrics, Precision, recall, F1 score and AUC has 94%, 90%, 92% and 98% respectively. Also by employing advanced deep learning models and carefully designing the training process, we were able to achieve high accuracy and performance in the classification task. The evaluation metrics demonstrated the effectiveness of the models in capturing and distinguishing the target classes. Despite the limitations associated with resource availability and cost on Google Colab, the project yielded valuable insights and demonstrated the potential of deep learning techniques in the domain. Moving forward, further optimizations in terms of computational resources and model architecture could enhance the scalability and applicability of the project in real-world scenarios.

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