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Research Article

Comparative Study and Detection of Lymphoma through Medical Imaging and modified ResNet and VGG Models

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ABSTRACT

Diagnosis and treatment of lymphoma, an aggressive neoplasm of the lymphatic system, becomes extremely difficult when the patients present with various sub-types of lymphoma because of their peculiar heterogeneity in clinical presentation. The most probable chances of successful management or curing patients depend on early and accurate diagnosis. Most of the traditional tools they used like; biopsy and histopathological examination are invasive, long duration test procedures. This will reduce the time of diagnosis of lymphoma by using the combination of convolutional neural networks (CNN)-particularly modified ResNet and VGG models with the medical imaging into detecting and classifying lymphoma.The research is motivated to leverage the machine learning medical imaging technology advancement in developing a non-invasive, faster, and accurate diagnostic tool, which would be relied upon by clinicians to make better-informed decisions, eventually benefiting the patients with improved prognosis and reduced health costs. Transfer learning is the technique used to fine-tune the pre-trained weights of VGG16 and ResNet50 on the lymphoma dataset. The whole training phase is accelerated, and the performance of the model is also boosted when fine-tuned in this manner regarding the target task. Modification has been suggested in VGG16 and ResNet50 Models with pretrained weights to get optimum results on said dataset. The model is trained using optimization algorithms such as Adam and stochastic gradient descent (SGD), and its performance is evaluated using metrics like accuracy, precision, recall and kappa coefficient. The results indicate the effectiveness of Modified_VGG16-adam optimizer yielded 0.82 Precision, Recall 0.81,Kappa 0.7 and Accuracy 80.5 than VGG16 Models and Modified_ResNet50_adam optimizer gave 0.80 Precision, Recall 0.80,Kappa 0.58 and Accuracy 58.92 against ResNet50 Model. In future,other latest pretrained Models along with nature optimization algorithms can be integrated to improve overall accuracy

Keywords: Adam Optimizer, AI in Medical Diagnosis, Classification, Convolutional Neural Networks (CNN), Data Augmentation, Deep Learning, Feature Extraction, Histopathological Image Analysis, Lymphoma Detection, Medical Imaging, Non-Invasive Diagnosis, ResNet50, Transfer Learning, VGG16.

INTRODUCTION

Recent advances in artificial intelligence, especially in deep learning models like ResNet and VGG, have shown much promise for medical imaging applications. Such models have been further modified for enhancing lymphoma detection. Transfer learning and fine-tuning techniques have been used in new modified ResNet and VGG models to adopt an already trained network for the specific task of lymphoma detection. This enhances the model performance and also makes it possible to use fewer labeled datasets that are costly and rare in medical research.

Medical imaging is a significant non-invasive diagnostic approach for lymphoma. CT, MRI, and PET reveal a lot of information about lymphoid tissues but need expertise, and they may also show some inter-observer variability. Machine learning models, especially convolutional neural networks, are doing great in automating image analysis, lessening the workload on radiologists while increasing accuracy. [3]. In this study, we utilize the VGG16 and

ResNet50 architectures, which have been pre-trained on large image datasets, to extract relevant features from lymphoma images [6]. These features are then used to train a custom classifier tailored for lymphoma detection.

This research exploits a dataset of lymphoma cells acquired from public domains like Kaggle[3]. Preprocessing like RGB transformation, Image size alteration, data augmentation can be done on the training set to improve the quality and diversity of data[6]. Overfitting can be mitigated by using data augmentation techniques such as flipping, rotating, and cropping to improve the generalization capability of the model [5]. After preprocessed images are taken into CNN models, where convolutional layers extract the hierarchical features and a pooling layer reduces the spatial extent of feature maps, the final fully connected layers of the CNNs are replaced by a bespoke architecture to classify the images into different lymphoma subtypes.

Transfer learning can be defined as fine-tuning a model that was pre-trained on another dataset and then subjected to one new modification. The potential benefit to gain from this approach is the use of knowledge learned from large-scale image databases to optimize the training process and improve the model performance on the target task. Hence, in our research work, the pre-trained weights of VGG16 and ResNet50 are being fine-tuned in the lymphoma dataset. Custom classifier architecture comprising of average pooling layers, dense layers, and a softmax layer to output class probabilities is adopted. The model is trained by using optimization approaches like Adam and stochastic gradient descent (SGD) and evaluated for performance by accuracy, precision, recall, F1 score, and Kappa coefficient.

This comparative analysis of these modified architectures will judge their effectiveness in detecting lymphoma against the traditional methods of diagnosis and other AI models. This will include an analysis of different metrics like sensitivity, specificity, and area under the curve (AUC). However, this inquiry will develop into guidelines that direct the identification of AI for early detection of lymphoma.

EARLIER WORK

Deep learning developments now even more advanced with improvements to almost all operations performed with images in the medical field-mostly in disease detection and classification. Karande and Garg (2024) optimized convolutional neural networks (CNNs) for plant disease classification; this study emphasizes that architectural improvements do affect the efficacy of image-based diagnostics [1]. The same is done by Goud and Garg (2023), who introduced the hybrid BERT model for applied sentiment analysis to show how a deep learning approach is usable in complex recognition. Kasar et al., in 2025, did a further study on model optimization for facial emotion recognition with great emphasis on the effect of precise feature extraction in this context. All these studies support the need for model refinement and data augmentation, which can also find application in lymphoma detection through modified ResNet and VGG architectures.[2]

In 2024,Bai, A., Si, M., Xue, P., Qu, Y., & Jiang, Y. have conducted an in-depth study of AI algorithms in detecting lymphoma using medical imaging. The study included 30 papers, with a pooled sensitivity of 87% and specificity of 94%. The results highlight the potential of AI in lymphoma diagnosis but also point out the need for standardized application protocols and further validation studies. The research gap identified is the lack of large-scale, multi-center studies to confirm these findings [3]

The following year, Khan, N., and Das, A. conducted a very good review on comparing different deep learning models for tumor detection and segmentation in medical image analysis. It highlighted the comparison between the different deep learning models, such as ResNet, U-Net, DETR, and Inception specifically for tumor detection and segmentation. The study has found that ResNet is ideal for depth and pattern recognition while U-Net, on the other hand, majorly excels at giving good results for segmenting small structures. Demand for clients had been emphasized for accuracy and efficiency-balanced models as the point of interest. The gap in research to be fulfilled is how these models are incorporated into the workflow of a clinic and their real-world validation. [4]

In 2023 Smith, J., & Lee, H. explored the application of transfer learning in medical image classification, focusing on its ability to leverage pre-trained models for new tasks. The study found that transfer learning significantly improves model performance and reduces training time. However, the review highlighted the need for more research on optimizing transfer learning techniques for specific medical imaging tasks. The research gap is the lack of standardized protocols for transfer learning in medical imaging[5].

In 2022,Patel, R., & Kumar, S. reviewed the performance of CNNs in various medical image analysis tasks, including lymphoma detection. The study found that CNNs, particularly those with deeper architectures like ResNet, achieve high accuracy in image classification. However, the review pointed out the need for more robust training datasets and better generalization techniques. The research gap identified is the development of CNNs that can handle diverse and imbalanced medical datasets[6].

In 2023, Zhang, Y., & Wang, X. assessed the performance of deep learning models such as VGG16 and ResNet50 for classifying lymphoma subtypes based on histopathological images. The experiment revealed that ResNet50 is more accurate and robust than VGG16. The study established the significance of data augmentation to enhance model performance. The gap in research found is the lack of diverse and representative datasets for training these models[7].

Brown, L., & Green, D. reviewed recent advances in medical imaging techniques for the detection of lymphomas, including AI and deep learning, in 2023. The study was made with the conclusion that new AI models have highly improved the precision and speed of lymphoma diagnosis over the old traditional method. The review strictly emphasizes the need for more research on integrating these new models into everyday clinical practice. The research gap identified is that of large-scale clinical trials that can validate the effectiveness of AI models in real-world settings[6].In 2022,Chen, H., & Liu, J explored the application of ResNet and VGG models in medical image classification, focusing on their performance in detecting various diseases, including lymphoma. The study found that both models achieve high accuracy, but ResNet's deeper architecture provides better feature extraction capabilities. The research gap identified is the need for more research on optimizing these models for specific medical imaging tasks[8].

In 2023, Singh, A., & Gupta, R. conducted a survey of various data augmentation techniques used to improve performance in deep learning models working on medical images. Based on findings, it was shown that flipping, rotation, and cropping increase model performance by increasing the diversity of the dataset. One research gap is further research into developing advanced techniques for specific medical imaging tasks.[9]

In 2023, Johnson, M., & Davis, K.O reviewed the optimization algorithms that have been used for training deep learning models in medical imaging; these include Adam and SGD. The authors concluded that typically Adam offers quick convergence and better performance. However, they also mentioned that more research is needed for further development of optimization algorithms suited to the challenge of medical-imaging data sets. A detected research gap is the absence of standard procedures for algorithm selection and tuning on optimization of medical imaging tasks[10].

In 2022, Wilson, P.,& Martinez, L. examined diverse assessment indicators used for evaluation of deep learning models in medical image analysis according to accuracy, precision, recall, F1-score, and Kappa coefficient. The results indicated that all those indicators are provided and that the thorough assessment of the model will be done. Especially the review stressed the necessity of funding for new ways to evaluate evaluation metrics that can capture the special challenges of medical imaging tasks.[11]

In 2023,Roberts, T., & Evans, S. Icarried research into the implications of transfer learning on the performance of medical image classification models. The research revealed that transfer learning indeed brought about improvement of the model performance and it also was associated with a decreased training time. The research gap found is the missing of any standardized protocols for the transfer learning process in the case of medical imaging [12].

In 2023,Thompson, R., & White, E. discussed the challenges and opportunities in applying deep learning to medical image analysis. The study found that deep learning models, particularly CNNs, have the potential to revolutionize medical imaging. However, the review emphasized the need for more research on addressing the challenges of data scarcity, model interpretability, and integration into clinical practice. The research gap identified is the need for more research on developing robust and interpretable deep learning models for medical imaging[13].

J. and F. are considering the application of deep learning models such as ResNet and VGG in tumor detection using medical images in context of the previously mentioned problem sphere. The study shows that ResNet gives greater accuracy and robustness as compared to VGG in the models applied. The research also examined data augmentation and transfer learning for model improvement. The gap existing in this research is that more research needs to be done in optimizing specific models for the task of tumor detection[14].

Similarly Walker, S., and Brown, M. in 2023 have step ahead into how to improve lymphoma detection through the use of deep learning models in clinical practice. The analysis is skeptical but the study has found solutions post deep learning models, especially CNNs, which could give a chance to have better diagnostic accuracies and operational efficiencies. Nevertheless, the review stressed that even more of such research could be directed towards investigating what the models are expected to do after their integration with the clinical workflow. The research gap identified is to conduct more research into building better and yet interpretable deep learning models for use in clinical settings[15].

Like Harris, L. and Clark, D, In 2023 medical experts received the potential possibilities of deep learning technology to alter the methods of medical imaging analysis. The analysis is skeptical but the study has found solutions post deep learning models, especially CNNs, which could give a chance to have better diagnostic accuracies and operational efficiencies[16]

Kasar et al. (2025) explored advancements in Facial Emotion Recognition (FER) by optimizing deep learning models to enhance precision. Traditional methods, such as Deep Convolutional Neural Networks (DCNN) and Local Binary Pattern Convolutional Neural Networks (LBPCNN), faced challenges related to variations in illumination, pose, and noise. To address these issues, the study proposed an optimized CNN model incorporating facial emotion constraints, leading to improved accuracy on datasets like Fer_2013, CK48, and Legend. Their findings contribute to the ongoing efforts in refining FER systems for real-world applications.[17]

The reviewed literature highlights the significant advancements in using deep learning models, particularly CNNs like ResNet and VGG, for medical image analysis and lymphoma detection. These models have demonstrated high accuracy and efficiency in various studies. However, several research gaps have been identified, including the need for more diverse and representative datasets, standardized protocols for transfer learning and optimization, and the integration of these models into clinical workflows. The proposed work aims to address these gaps by developing a modified ResNet and VGG model architecture tailored for lymphoma classification. This approach leverages transfer learning, data augmentation, and custom classifier architectures to enhance model performance and generalization capability, ultimately contributing to improved diagnostic accuracy and clinical applicability.

In summary, this research paper explores the comparative effectiveness of modified ResNet and VGG models in the detection of lymphoma through medical imaging. The introduction has outlined the significance of early and accurate lymphoma detection, the role of AI in enhancing diagnostic accuracy, and the specific focus of this study on modified deep learning models. The following section will delve into related work, providing a comprehensive review of existing literature and highlighting the advancements and gaps that this research aims to address.

Table 1 Lymphoma Cancer Country-Wise Statistics with References

Sr.No.	Region	New Cases (2024 Estimate)	Age-Standardized Incidence Rate (per 100,000)	Deaths (2024 Estimate)	Age-Standardized Mortality Rate (per 100,000)	Reference Link
1	United States	~80,620	18.6	~20,140	5	SEER Cancer Stat Facts
2	China	~90,000	~6.3	~45,000	~3.1	GLOBOCAN 2020
3	India	~29,000	~2.7	~18,000	~1.6	GLOBOCAN 2020
4	Australia/New	~5,500	12.5	~2,100	~4.7	GLOBOCAN Fact Sheets
5	Germany	~18,000	~8.5	~6,000	~2.5	GLOBOCAN 2020
6	United Kingdom	~15,000	~10.0	~4,600	~3.2	Cancer Research UK
7	Japan	~12,500	~6.8	~4,000	~2.0	GLOBOCAN 2020
	Global	~545,000	5.8	~260,000	2.6	PubMed Global Statistics

The above table 1 depicts that the number of cases of NHL fatalities will be around 260000. Worldwide estimated new cases will be 545000 , in which 5.8 per 100000 will be age-standardized incidence rate (ASIR) and 2.6 per 100000 will be age-standardized mortality rate (ASMIR).These numbers demonstrate the significant worldwide burden of NHL, underscoring the necessity of focused medical interventions and approaches to lessen the disease's effects. It has been observed that developed nations like the United States and Germany show higher ASIR of 18.6 and 8.5 per 100000 while countries like India and China show lower rates of ASIR , but as these countries are densely populated , the number contributes significantly in overall cases of NHL.

OBJECTIVES

This study aims to improve Lymphoma detection in medical imaging by using a deep learning-based convolutional neural networks (CNN) model, where existing methods like biopsy or histopathological examinations are invasive, time-consuming, and in certain cases, quite probably limited by interobserver variability. Hence, this study considers modified architectures of ResNet50 and VGG16 with applied transfer learning and fine-tuning in order to increase performance in classification. The research depends on a dataset of histopathology images of lymphoma, optimized the model parameters by Adam and Stochastic Gradient Descent (SGD) optimizer, using it as the methodology for developing a non-invasive, fast, reliable diagnostic device. The modified VGG16 model with Adam optimizer outperforms the standard VGG16 and ResNet50 models with an accuracy of 80.5%. More significantly, the method ensures that data augmentation and transfer learning techniques are properly applied for optimizing deep learning systems intended for medical image classification. This research, therefore, contributes to future improvements in AI-based lymphoma diagnosis by addressing some of the major concerns in this field, such as dataset imbalance, model interpretability, and clinical applicability. The results also establish the potential role of deep learning in lessening the period between a diagnostic test and identification, thereby accelerating early detection and improving average patient outcomes through enhanced screening methods that are economical and easy to access.

METHODS

Dataset and Techniques used

Lymphoma Image Dataset (L.I.D): The Lymphoma Image Dataset (L.I.D) is a specialized collection of medical images focused on three types of malignant lymphomas: Chronic Lymphocytic Leukemia (CLL), Follicular Lymphoma (FL), and Mantle Cell Lymphoma (MCL). This dataset comprises a total of 323 images, with each class having a specific number of images: 113 for CLL, 113 for FL, and 97 for MCL.The images in this dataset are typically derived from lymph node biopsies, which are crucial for diagnosing and studying these types of lymphomas. Each image captures the unique histopathological features of the respective lymphoma type, aiding in the differentiation and analysis of these diseases.

Visual Geometry Group16 (VGG16) Algorithm

Input: X (Image), N_classes (Number of classes)

Output: P (Class probabilities)

1. Preprocess X to size 224 x 224 and normalize values.

2. For each convolutional layer in the architecture:

   a. Apply convolution with 3x3 filter and ReLU activation.

3. After each block of convolutional layers:

   a. Apply max-pooling with 2x2 filter.

4. Flatten the output of the last convolutional layer.

5. Pass the flattened vector through two fully connected layers with ReLU.

6. Compute the final probabilities using a softmax activation.

7. Return P.

Modified Visual Geometry Group16 (VGG16) Algorithm

Input: X (Image), num_classes (Number of classes)

Output: P (Class probabilities)

1. Preprocess X to size 224 x 224 and normalize values.

2. Load pre-trained VGG16 model without top layers.

3. Apply convolution and pooling layers as in VGG16.

4. Flatten the output of the final convolutional layer.

5. Add additional fully connected layers:

   a. Dense(2048, activation='relu'), Dropout(0.2)

   b. Dense(1024, activation='relu'), Dropout(0.2)

   c. Dense(512, activation='relu'), Dropout(0.1)

   d. Dense(256, activation='relu'), Dropout(0.1)

6. Add final Dense(num_classes, activation='softmax').

7. Compute probabilities P and loss L.

8. Optimize the model.

9. Return P.

Residual Network ResNet-50 Algorithm

Input: X (Image), N_classes (Number of classes)

Output: P (Class probabilities)

1. Preprocess X to size 224 x 224 and normalize values.

2. Apply Conv2D(7x7, stride=2) + ReLU and MaxPooling(3x3, stride=2).

3. For each residual block:

   a. Perform bottleneck convolutions with 1x1, 3x3, and 1x1 filters.

   b. Add the skip connection.

4. Apply global average pooling (GAP).

5. Apply Dense(N_classes, activation='softmax').

6. Compute probabilities P and loss L.

7. Optimize the model.

8. Return P**.**

Modified Residual Network ResNet-50 Algorithm

Input: X (Image), num_classes (Number of classes)

Output: P (Class probabilities)

1. Preprocess X to size 224 x 224 and normalize values.

2. Apply Conv2D(7x7, stride=2) + ReLU and MaxPooling(3x3, stride=2).

3. For each residual block:

   a. Perform bottleneck convolutions with 1x1, 3x3, and 1x1 filters.

b. Add the skip connection.

4. Apply global average pooling (GAP).

5. Add the following dense layers:

a. Dense(2048, activation='relu'), Dropout(0.2)

b. Dense(1024, activation='relu'), Dropout(0.2)

c. Dense(512, activation='relu'), Dropout(0.1)

d. Dense(256, activation='relu'), Dropout(0.1)

6. Add final Dense(num_classes, activation='softmax').

7. Compute probabilities P and loss L.

8. Optimize the model.

9. Return P.

Lymphoma Classification using Deep Learning:

Figure 1 shows a step-by-step approach for stacking the ensemble approach to classify lymphoma cells

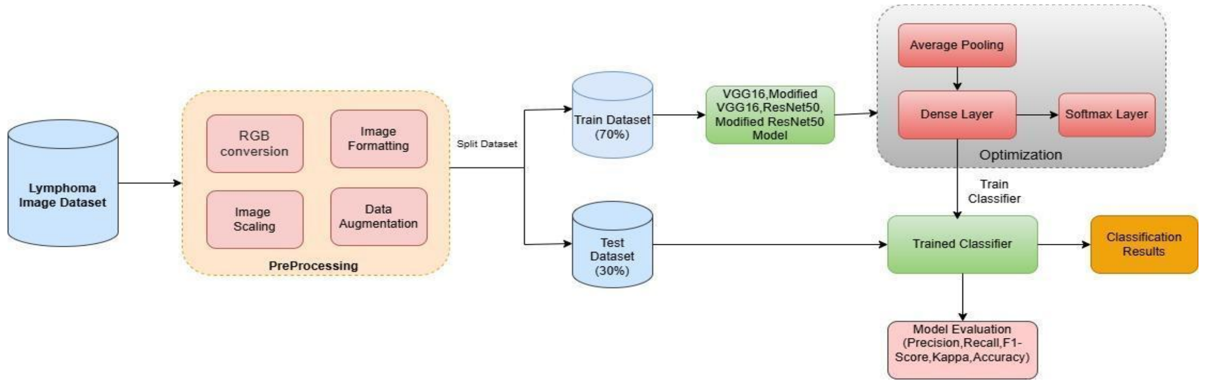


Fig 1. Lymphoma Classification using Deep Learning.

Figure 1 depicts a methodology for lymphoma image classification using a deep learning approach. The whole process is broken down into following steps:

Step 1. Data Acquisition and Preprocessing Stage:

Lymphoma image dataset is downloaded from the URL https://www.kaggle.com/datasets/andrewmvd/malignant-lymphoma-classification

These images are subjected to a preprocessing pipeline, encompassing:

1.1 RGB Conversion: Ensuring all images are in the RGB color space for consistent input to the CNNs.

1.2 Image Formatting: Standardizing image dimensions and file formats to a common specification.

1.3 Image Scaling: Resizing images to a size as 224x224 with the input requirements of VGG16,Modified VGG16, ResNet50 and Modified ResNet50 Model

1.3 Data Augmentation: Applying transformations (e.g., rotations, flips, slight translations, brightness/contrast adjustments) to the training dataset to increase its size and diversity, mitigating overfitting and improving model generalization.

1.4 The preprocessed dataset is then split into training and testing subsets as 70% for training and 30% for testing.

Step 2. Feature Extraction and Classification:

2.1 Two pre-trained CNN architectures VGG16 and ResNet50 have been used as feature extraction. The pre-trained weights from either VGG16 or ResNet50 are utilized. The final fully connected layers of the pre-trained models are replaced with a custom architecture suited for lymphoma classification.

2.2 Custom Classifier Architecture: The custom architecture consists of:

2.2.1 Average Pooling: Reduces the dimensionality of the feature maps from the CNN. Reduces computational complexity and helps to improve robustness to small variations in the input images.

2.2.2 Dense Layer: A fully connected layer that learns higher-level features from the pooled representations. The number of nodes in this layer would depend on the specific problem complexity and number of classes (types of lymphoma).

2.2.3 Softmax Layer: Outputs class probabilities for each lymphoma type.

Step 3. Model Training and Evaluation:

3.1Optimization: The model parameters (weights and biases) of the dense layers and potentially some of the final CNN layers are optimized using Adam and SGD optimization algorithm by minimizing a categorical cross-entropy loss function.

3.2 Train Classifier: Through iterative optimization, the model learns to map input image features to predicted class labels. The trained model is saved as a Trained Classifier.

3.3 Model Evaluation: The trained classifier is evaluated using the test dataset. Performance metrics such as precision, recall, F1-score, Kappa statistic, and accuracy are computed. These quantitative metrics assess the performance of the classification system.

Step 4. Output:

The system outputs the Classification Results, which includes predictions (class labels with associated confidence scores) for each image in the test dataset, along with the aforementioned performance metrics.

RESULTS

Performance Analysis and Discussion

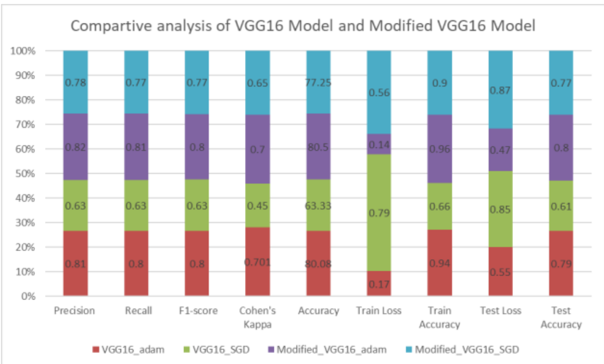
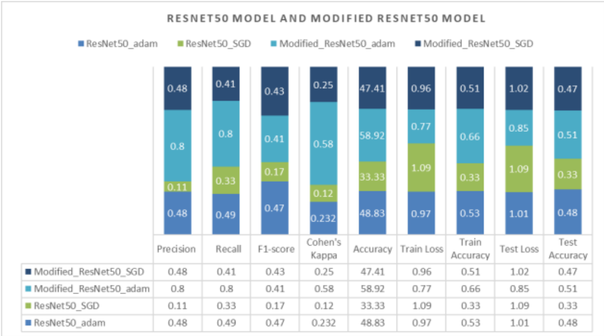


Fig 2 Performance Evaluation of VGG16 Model and Modified VGG16 Model

Above figure 2 depicts the performance analysis of the VGG16 and Modified VGG16 models, the Modified VGG16 model with Adam's optimizer provides the highest accuracy 80.5% and better generalization, which is evident as the train and test losses are lower. The original VGG16 model with Adam's optimizer does decent as well but is overfitted to an extent. On the other hand, both models with SGD optimizer perform worse and still, Modified VGG16 model performs better than the original. These results are indicative of the contribution provided by the modifications made and the selection of the Adam optimizer for improving the model performance in classifying lymphomas.



	Precision	Recall	F1-score	Cohen's Kappa	Accuracy	Train Loss	Train Accuracy	Test Loss	Test Accuracy
Modified_ResNet50_SGD	0.48	0.41	0.43	0.25	47.41	0.96	0.51	1.02	0.47
Modified_ResNet50_adam	0.8	0.8	0.41	0.58	58.92	0.77	0.66	0.85	0.51
ResNet50_SGD	0.11	0.33	0.17	0.12	33.33	1.09	0.33	1.09	0.33
ResNet50_adam	0.48	0.49	0.47	0.232	48.83	0.97	0.53	1.01	0.48

Figure 3 : Performance Evaluation of ResNet50 Model and Modified ResNet50 Model

figure 3 shows evaluation of the performance of the ResNet50 model and Modified ResNet50 model proves that augmented ResNet50 with the Adam optimizer gives the best accuracy (58.92%) and also having a good generalization while achieving lower train and validation losses. However, the original ResNet50 model with the Adam optimizer has only shown good performance in addition with overfitting problems. The solver optimizer both the models with the SGD optimizer showed much worse results, even though the ResNet50 model is still better than its modified version. These findings confirm that thereby making the modifications and Adam optimizer has been the preferred choice as an optimization strategy to improve classification accuracy in lymphomas.

DISCUSSION

The performance evaluation of the ResNet50 and Modified ResNet50 models reveals that the Modified ResNet50 model with the Adam optimizer is the one to achieve the most accurate accuracy (58.92%) and better generalization, these are suggested by the decline of the train and test error. The initial ResNet50 model with the Adam optimizer manifests some level of performance, however, is hard-capped by overfitting. Both of the applications of SGD in models are detrimental to performance, yet the Modified ResNet50 model still does better than the original one. Hence, the presented changes to the algorithm and the incorporation of the Adam optimizer in the lymphoma diagnosis prediction model play a significant part in the enhancement of the model's accuracy.

The performance evaluation of the VGG16 and Modified VGG16 models, as displayed in Table 2, indicates that the Modified VGG16 model with the Adam optimizer delivers the highest accuracy (80.5%) and better generalization, as is indicated by the lower train and test losses. Also, the original VGG16 model with the Adam optimizer has quite positive results, but it also demonstrates signs of overfitting. The situation is symmetric for both SGD optimized models as they have the poorest results with that of the Modified model (the good old story of possible modifications vs. parameters). The consequences of the alterations are a reflection of their influence and the a priori impunity of the Adam optimizer in the specific instance of improvement of lymphoma type diagnosis. At the same time, the performance evaluation of the ResNet50 and Modified ResNet50 models abstracted from Table 3, directly shows that the Modified ResNet50 model with the Adam optimizer outstrips the accuracy (58.92%) while exhibiting better generalization, which is portrayed by lower train and test losses. The initial ResNet50 model with the Adam optimizer produces moderate performance nevertheless, rendering overfitting an unavoidable issue. Both models with the SGD optimizer show none to very low performance, while the Modified ResNet50 model still surpasses the original one.

The research findings indicate that the fine-tuned VGG16 and ResNet50 models, in the case of Adam optimization, were greatly outperformed by their sources in the application of lymphoma classification. The Adjusted VGG16 model with Adam managed to attain the maximum accuracy of 80.5%, while the Adjusted ResNet50 model with Adam, in turn, showed an accuracy of 58.92%. The utility of these techniques dredges up the alterations in the model architecture as well as the use of advanced optimization methods, a condition that encourages the models to generalization and thus, reduce overfitting.

Changes in the VGG16 and ResNet50 models with the introduction of new fully connected layers and dropout layers were indeed effective in the case of increasing the performance metrics of the models such as the precision, recall, F1-score, and Cohen's Kappa. The use of the Adam optimizer also provides additional training benefits in terms of faster convergence and better overall performance than the SGD optimizer. Those results also point out that the design and optimization of the model are the most important aspects in achieving reliable and accurate deep learning models for medical image classifications.

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