



Deep Learning Based White Blood Cancer Detection In Bone Marrow Using Histopathological Images

Ms. Sunitha N V¹, Pranav Joshi², Rakesh Kumar³, Raksha S Shetty⁴, Raksha M Suvarna⁵

Assistant Professor, Dept. of Computer Science & Engineering, Mangalore Institute of Technology & Engineering, Moodabidre, India¹

Student, Dept. of Computer Science & Engineering, Mangalore Institute of Technology & Engineering, Moodabidre, India^{2,3,4,5}

ABSTRACT: This work has employed a deep learning strategy to automatically detect and classify white blood cell (WBC) cancers, including leukemia, using histopathology images. This technique analyses histopathological images and uses convolutional neural networks (CNNs) to accurately detect distinct WBC cancer subtypes. When compared to pathologists who manually read cases, our method provides answers more quickly and accurately. Tested extensively on multiple datasets, our method consistently outperforms existing methods in terms of sensitivity, specificity, and overall accuracy. The study has also been made to improve the effectiveness of transfer learning techniques, which allow our model to adapt and perform well on different datasets. Because of its versatility, it can be applied in real-world clinical settings, which has the potential to revolutionize personalized medicine approaches to WBC cancer diagnosis and treatment. Additionally, our method employs explainable AI techniques to give doctors greater assurance and understanding by revealing the model's decision-making process. More informed treatment decisions by healthcare professionals lead to better outcomes for patients with WBC malignancies. By combining advanced deep learning methods with interpretable models, our research provides a significant step toward integrating AI-driven treatments into standard clinical practice. This has the potential to significantly improve patient care and outcomes in the field of oncology.

KEYWORDS: White Blood Cancer Detection, Artificial intelligence, Deep learning, Histopathological Images, Convolutional Neural Networks (CNNs), Benign, Malignant, Rank-Based Ensemble, Inceptionv3, Xception, MobileNet

I.INTRODUCTION

White blood cell (WBC) malignancies, which include lymphoma and leukemia, are a hard field in oncology because of their wide variety of subtypes, inconsistent clinical presentation, and difficult diagnostic procedures. Initiating suitable treatment options and improving patient outcomes depend on the quick and correct detection of these cancers. A crucial component of diagnosing WBC cancer continues to be the histopathological analysis of blood smears, which provides invaluable information about the distribution and morphology of cells. However, the labor-intensive, subjective, and subject to observer variability manual interpretation of histological pictures by skilled pathologists may result in inconsistent diagnoses and delays in therapy.

The field of medical image analysis has undergone a significant transformation with the introduction of deep learning techniques, specifically convolutional neural networks (CNNs), which have automated feature extraction and classification tasks. These AI-driven methods have great potential to improve the precision, effectiveness, and repeatability of cancer diagnosis, particularly malignancies of the white blood cells. Deep learning algorithms may detect fine patterns and subtle differences indicative of many cancer subtypes by utilizing large-scale annotated histopathology datasets, outperforming conventional diagnostic methods in this regard.

Our main goal in this work is to create a deep learning system that is broad enough to automatically identify and classify WBC tumors from histopathology pictures. By using CNNs, the study aims to lessen the difficulties involved in manual interpretation and provide a reliable and scalable method for diagnosing WBC cancer. Our approach employs methodical



training, rigorous validation, and extensive testing process on various datasets to assess the effectiveness and applicability of the suggested model. Furthermore, the aim is to investigate sophisticated transfer learning methods to improve the model's flexibility to different datasets and clinical situations, leading the field of WBC cancer detection and therapy toward more individualized and efficient methods.

Furthermore, our results emphasize the necessity of employing explainable AI techniques, providing insights into the model's decision-making processes. More interpretability and transparency as well as helpful information to assist in selecting therapies that are suitable for each patient's needs are advantages that clinicians enjoy. Our research marks a substantial advancement in the smooth incorporation of AI-powered solutions into standard clinical procedures, which will eventually enhance oncology patient care and outcomes. Interpretable models are used with cutting-edge deep learning methods to achieve this.

II. LITERATURE SURVEY

Kumar et al. [1] proposed a study that employs convolutional neural networks (CNNs) on the SN-AM dataset to classify Acute Lymphoblastic Leukemia (ALL) and Multiple Myeloma (MM). The CNN model achieves an impressive 97.2% overall accuracy by using picture pre-processing for feature extraction and error reduction, and data augmentation for generalization. It solves issues like inconsistent manual classification and is inexpensive and quick to deploy. The model is shown to be superior to some state-of-the-art CNN models through comparative analysis. Accuracy, precision, recall, sensitivity, and specificity are some of the evaluation measures. Furthermore, the model demonstrates adaptability as it achieves high classification accuracies across various datasets. Overall, the work offers a strong automated classification technique that uses CNNs to detect white blood cell malignancy, showing promise for real-world application.

Manna et al. [2] Computer-Aided Diagnosis (CAD) systems were developed for early diagnosis of cervical cancer, a major health concern that takes over 0.3 million lives yearly. In this paper, an ensemble-based classification model for Pap stained single cell and whole-slide image classification is presented, utilizing three pre-trained CNN architectures (Inception v3, Xception, and DenseNet-169). The model achieves good sensitivity and accuracy on benchmark datasets by adding confidence in base classifier predictions. The SIPaKMeD Pap Smear dataset is notable for its 98.55% accuracy and 98.52% sensitivity in a 2-class context, as well as 95.43% accuracy and 98.52% sensitivity in a 5-class environment. It achieves 99.23% sensitivity and accuracy on the Mendeley LBC dataset. Overall, the model shows potential in cervical cytology classification, outperforming numerous cutting-edge methods.

Zakir Ullah et al. [3] have put forward a study that discusses the need for less intrusive and faster ways to identify acute lymphoblastic leukemia (ALL), which is a frequent bone marrow type of the disease. The need for alternatives is being driven by the slowness and agony of traditional procedures, such as bone marrow and blood investigations. Using medical images, a CNN-based method is suggested, which combines the VGG16 architecture with an attention module (ECA) to extract better deep features. Techniques for augmentation increase both the volume and quality of training data. The CNN model achieves 91.1% accuracy in differentiating between normal and malignant cells using the C-NMC dataset. In order to improve the accuracy of ALL diagnoses, the research highlights the shortcomings of earlier approaches and advocates for high-performance algorithms based on bigger datasets and automated feature extraction.

Prellberg et al. [4] In order to detect acute lymphoblastic leukemia (ALL) from microscopic images, a ResNeXt convolutional neural network with Squeeze-and-Excitation modules is presented in this paper. The method works, as evidenced by an 88.91% weighted F1-score on the C-NMC online challenge test set. A thorough description of the dataset and a plan for data augmentation are given. The work emphasizes how crucial big datasets, like as C-NMC, are to the advancement of ALL categorization. The effectiveness of the suggested strategy is demonstrated by a comparative analysis with other approaches found in the literature. Convolutional neural networks are used in this paper to propose a straightforward yet efficient ALL classification approach that produces encouraging results on the C-NMC dataset.

Chen et al. [5] The use of the Taguchi approach and a Resnet ensemble model for the classification of acute lymphoblastic leukemia (ALL) in microscopic pictures is discussed in the paper. Classification mistakes can be reduced by utilizing an



ensemble model, even though previous research has mostly concentrated on individual models. It draws attention to the paucity of research on ensemble models and the impact of hyperparameters on the accuracy of pre-trained CNN models. Pre-trained CNNs have been employed in related studies for the categorization of ALL in pictures from bone marrow and blood smears. The suggested ensemble model Resnet101-9 outperforms individual models on a variety of measures, achieving 85.11% accuracy and an 88.94% F1-score in classifying ALL in microscopic pictures. The study demonstrates that in order to improve the accuracy of ensemble models' picture categorization, it is crucial to choose appropriate algorithm hyperparameters and implement a majority voting method.

III. SCOPE AND METHODOLOGY

Aim of the project

The aim of this project is to create a deep learning system that can automatically identify Acute Lymphoblastic Leukemia (ALL) in bone marrow samples using histopathological pictures in an accurate and fast manner. This entails gathering a varied dataset of bone marrow sample histopathology images, standardizing image formats using preprocessing techniques, and putting quality control mechanisms in place to guarantee the consistency and correctness of the dataset. The research also intends to investigate several feature extraction methods for the analysis of histopathology pictures, with a focus on convolutional neural networks (CNNs). The main goal is to distinguish between benign and malignant cells in order to precisely determine whether or not ALL cancer cells are present in bone marrow histopathology images. In addition, the research aims to create a rank-based ensemble of CNN models that can accurately distinguish between malignant and benign cells with a high degree of precision by recognizing cancerous regions within histological pictures of bone marrow samples.

Scope of the Project

The scope of this study is to use histopathological pictures to automatically detect acute lymphoblastic leukemia (ALL) in bone marrow samples using a deep learning-based method. The technique entails gathering a dataset of labeled photos that show different ALL phases and subtypes, then preprocessing the photographs to improve and standardize their quality. Convolutional neural networks (CNNs), in particular, are deep learning models that will be taught to reliably categorize leukemia cells. Model performance will be evaluated against manual diagnostic approaches using evaluation metrics, and clinical utility will be improved using interpretability strategies. Its scalability and generalizability across a range of clinical circumstances and patient demographics will be assessed, and deployment issues for real-world integration will also be examined.

Methodology

The system used a methodical approach in our technique to develop and assess our white blood cell cancer detection technology. The process started with the painstaking curation of a heterogeneous dataset containing histological pictures of malignancies of the white blood cells. Then the preprocessing methods to improve the quality of the images and standardize the features are done so that the analysis could be done efficiently. Next, the three different convolutional neural network (CNN) models: MobileNet, Xception, and InceptionV3 are developed and optimized. To speed up training and improve performance, these models are initialized with pre-trained weights using transfer learning. Throughout the training process, a close eye was kept on the models' development, and any necessary hyperparameter tweaks were made to maximize performance.

Then each CNN model's performance after training is rigorously assessed by utilizing recognized criteria such as accuracy, precision, recall, and F1 score. To evaluate generalization skills and find any problems like overfitting or underfitting, the dataset was divided into distinct training, validation, and testing sets. In order to assess the advantages and disadvantages of each CNN design, extensive comparative studies were also carried out, taking into account variables like interpretability, classification accuracy, and computational efficiency. Our decision regarding which model would work best for practical implementation in clinical settings was made with this analysis in mind. Our goal was to create a reliable and efficient system for detecting white blood cell cancer by using this methodical approach, which would ultimately lead to better patient outcomes in the field of oncology.



System Architecture

Our system for detecting cancer in white blood cells is built with an architecture that makes it easier for users to interact with the computational components that underpin it. Uploading histopathology pictures and viewing classification results are made simple with the system's web-based interface. Deep learning architectures-trained machine learning models are used by server-side components to handle processing and classification tasks. To identify whether anomalies are benign or cancerous, these models examine uploaded photos. Data management modules are also incorporated into the architecture to effectively manage the preprocessing, retrieval, and storage of histopathology images. All in all, the system architecture has been painstakingly designed to satisfy the requirements of actual healthcare settings, offering precise, effective, and expandable solutions for the detection of white blood cell cancer.

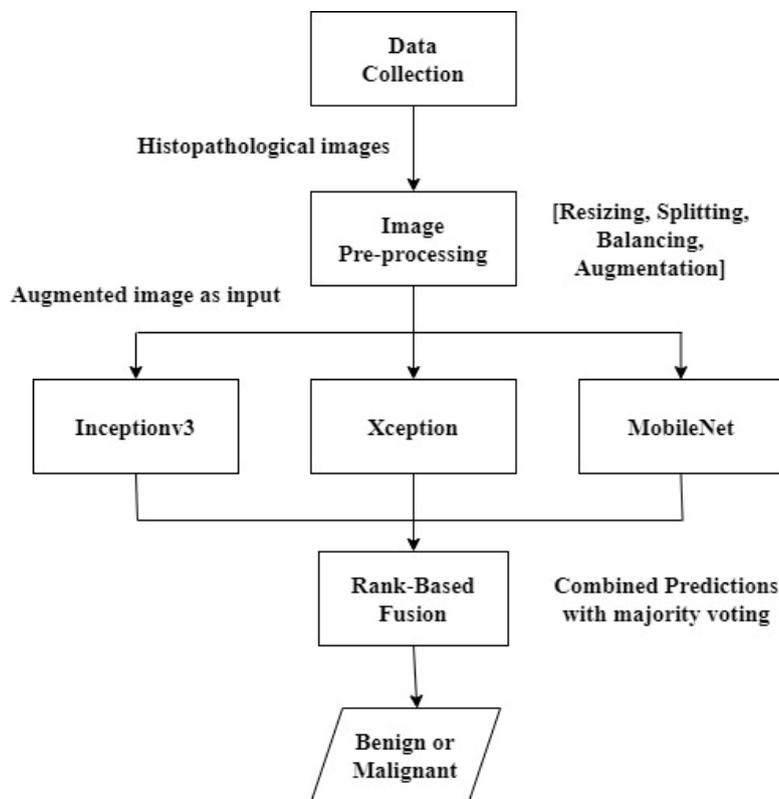


Fig 1. System Architecture

IV. CONCLUSIONS

Our study's findings demonstrate the value of using cutting-edge computer methods, in particular convolutional neural networks, to improve the precision of white blood cell cancer diagnosis. This technology presents promising opportunities to enhance diagnostic results by decreasing human error and unpredictability in picture interpretation. This project can be further validated and improved in order to make sure that it can be used in a variety of patient demographics and healthcare environments. Researchers, physicians, and industry stakeholders must work together to ensure that this technology is seamlessly incorporated into standard clinical practice. Furthermore, in order to promote broad acceptance and optimize patient benefits, it is imperative to give priority to solutions that are easily understood and accessible.



REFERENCES

- [1] Kumar, D., Jain, N., Khurana, A., Mittal, S., Satapathy, S. C., Senkerik, R., & Hemanth, J. D. (2020). Automatic Detection of White Blood Cancer From Bone Marrow Microscopic Images Using Convolutional Neural Networks. *IEEE Access*, 8, 142521–142531. <https://doi.org/10.1109/access.2020.3012292>
- [2] Manna, A., Kundu, R., Kaplun, D., Sinitca, A., & Sarkar, R. (2021, July 15). A fuzzy rank-based ensemble of CNN models for classification of cervical cytology. *Scientific Reports*, 11(1). <https://doi.org/10.1038/s41598-021-93783-8>
- [3] Zakir Ullah, M., Zheng, Y., Song, J., Aslam, S., Xu, C., Kiazolu, G. D., & Wang, L. (2021, November 12). An Attention-Based Convolutional Neural Network for Acute Lymphoblastic Leukemia Classification. *Applied Sciences*, 11(22), 10662. <https://doi.org/10.3390/app112210662>
- [4] Prellberg, Jonas & Kramer, Oliver. (2019). Acute Lymphoblastic Leukemia Classification from Microscopic Images Using Convolutional Neural Networks. 10.1007/978-981-15-0798-4_6.
- [5] Chen, Yao-Mei & Chou, Fu-I & Ho, Wen-Hsien & Tsai, Jinn-Tsong. (2022). Classifying microscopic images as acute lymphoblastic leukemia by Resnet ensemble model and Taguchi method. *BMC Bioinformatics*. 22. 10.1186/s12859-022-04558-5.