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Intelligent Multi-Model Deep Learning Approach for Accurate Leukaemia Diagnosis and Stage Classification

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Abstract: Leukaemia, a malignant disorder of the blood and bone marrow, requires early and accurate detection to improve patient survival and treatment planning. Traditional manual examination of peripheral blood smears is labour-intensive, prone to errors, and subject to observer variability. This study proposes an automated framework for leukaemia detection and stage prediction using multi model convolutional neural networks with transfer learning. Four pre-trained architectures—ResNet50, DenseNet121, MobileNetV2, and EfficientNetB3—are fine-tuned on microscopic blood smear images to classify healthy and leukemic cells as well as predict disease stages. Each model is evaluated across standard performance metrics, with accuracy considered the primary benchmark for model selection. Experimental results reveal that among the tested architectures, this model achieving the highest accuracy emerges as the optimal choice for reliable leukaemia detection and stage prediction.

Keywords: Leukemia Detection, Stage Prediction, CNNs, Transfer Learning, MobileNetV2.

1. Introduction

Leukemia is a life-threatening blood cancer which is to be diagnosed early and precisely. Old diagnostic techniques are manual, time consuming, and can result in the creation of errors. Medical data can be analyzed using deep learning techniques at a high accuracy. The project employs multi-model deep learning technology to enhance the diagnostic outputs. Several models are used to improve reliability and limit misclassification. The system identifies leukemia and categorizes the stages well.

The strategy aids physicians through quicker and improved decision-making. On balance, the project raises the issue of AI as a source of healthcare diagnostics enhancement. Leukemia is a severe type of cancer, which develops in the bone marrow and interferes with the development of blood cells. The correct diagnosis of the type of leukemia and its stage of development is critical in the choice of the treatment course and better patient outcomes. Nonetheless, traditional diagnostic methods usually rely on the analysis provided by experts that might be laborious and subject to experience and observation. The intensive development of deep learning and medical imaging technologies has provided opportunities in the field of intelligent diagnosis of a disease.

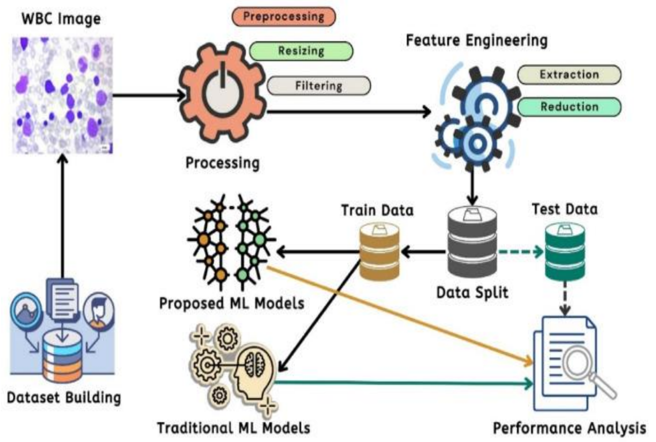

Figure.1 Leukemic Cancer Detection in Microscopic Blood Samples

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Multi-model deep learning model builds upon multiple neural networks by utilizing their edge in taking different aspects of edical data, resulting in more accurate and reliable predictions. These models are particularly useful with the complicated visual patterns of leukemia in blood cells. This is a smart way of detecting leukemia as well as classifying its stage by making a combination of superior learning models into a single system. It is expected that the proposed approach will help patients deal with leukemia and further contribute to patient-centered care by increasing the efficiency of the diagnosis [Figure.1], reducing human reliance, and eliminating delays during leukemia diagnostics.

2. Literature Survey

Due to the growing demand for identifying leukemia at its earliest and most accurate stages, there is now considerable research being conducted into the use of medical imaging and artificial intelligence as tools for researching leukemia. In recent years, researchers have focused on using traditional machine learning techniques, as well as developing new methods for processing images using deep learning, with the ultimate goal being to develop technologies that will help to improve both the accuracy of diagnostic processes and reduce the need for human involvement [1]. The present literature review explores the key fields of research contribution to leukemia detection and stage classification with specific references to deep learning and multi-model techniques. Past studies regarding leukemia diagnosis relied more on blood smears examination by the hematologists using manuals [2]. Although this was effective, this was a time-consuming process which was prone to inter-observer variability. To overcome these limitations, researchers suggested computer-aided diagnosis systems which are classical image processing systems. Such methods typically involve pre-processing images, white blood cell location, features, and neural networking using machine learning algorithms.

The morphological operations and color-based segmentation as well as the thresholding and edge detection techniques were widely used to isolate the leukemic cells in blood smear images [3]. The extracted features included shape, texture, color intensity, and nucleus to cytoplasm ratio. Popular classifiers include Support Vector Machines, K-Nearest Neighbors, Decision Trees, and Naive Bayes [Figure.2]. Though such techniques were quite effective, they relied on the quality of hand and images, which minimized their power and capacity to scale to great balances. Machine Learning-Based Detection of Leukemia: Due to the emergence of machine learning, researchers began to use the concepts of supervised learning to improve the quality of the classification of leukemia [4]. The study indicated that SVM and Random Forest classifiers could achieve reasonable accuracy provided that a combination is made with a well selected set of features. Dimensionality reduction techniques of Principal Component Analysis (PCA) and selection were a popular further way to enhance the performance of classifications, however, required much domain knowledge to engineer features, and were not able to handle more complex morphological variations in cells [5]. Moreover, most of the models applied in machine learning were able to only do binary classification, e.g. leukemic and normal cells but not leukemia subtype and stage. The given problems prompted the application of the deep learning algorithms which can learn the discriminative features themselves, without any processing of the raw information.

Deep Learning in Leukemia Diagnosis: Deep learning in the medical image analysis to enable end-to-end learning and feature extraction by features markers that are not machine-based. Convolutional Neural Networks were widely applied to identify leukemia due to the great degree of learning spatial and hierarchical image features. Some of the works have employed CNN structures to distinguish normal blood smears and leukemic ones, and the precision of the work is far better than the classical ones. Pre-trained deep learning models used in transfer learning include VGGNet, ResNet, Inception, DenseNet, and AlexNet. Once the leukemia datasets had been optimized using these models, scientists were able to achieve an improved performance despite the scarcity of medical data [6]. These models could be highly generalized and take less time to train. Multi-class classification systems provided a more accurate diagnostic information, which assists clinicians with the treatment plan.Stage Classification and Severity Analysis: Stage classification besides the detection of leukemia is a significant research issue given that it seeks to search the levels of disease stages. In other studies, clinical parameters and laboratory results of tests and image data were used in order to predict leukemia stages. The Recurrent Neural Networks and Long Short-Term Memory networks were used to study sequential clinical data and patterns of diseases course [7].

The current leukaemia diagnosis and stage classification systems primarily rely on the old medical analysis practices and primitive forms of computing. Such systems are designed to identify abnormal white blood cells and help physicians ensure that leukemia is present. Despite being useful in the diagnosis, they have a number of limitations on accuracy, speed, and detailed stage classification [8].

Manual Diagnosis Systems: The most prevalent system available is the manual review of blood smear image and bone marrow samples under the scrutiny of trained pathologists. Microscopes are used to examine cell morphology, size, shape and distribution by doctors. Other laboratory tests like Complete Blood Count (CBC) and flow cytometry help in supporting the diagnosis. Although

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manual diagnosis can be trusted, it is very time consuming and it is expertly dependent [8]. The human fatigue, subjectivity, and inter observer variation can result in inconsistent outcomes, particularly in the early-stage leukaemia when the abnormal cells are similar to normal cells.

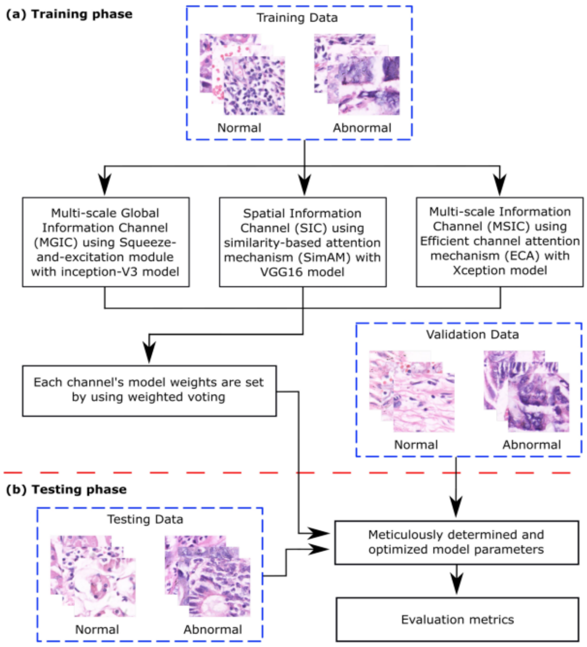

Figure. 2 Training and Testing Phases

2.1. Systems based on Image Processing

To minimize human intervention, conventional image processing-based systems were invented. The process of isolating white blood cells is done by using techniques like noise removal, contrast enhancement, thresholding, and morphological operations. Manual characteristics like cell area, nucleus shape, texture, and colour density were estimated and computed [9]. Despite the fact that these systems enhance speed in processing, their accuracy is very sensitive to image quality and set rules. They are not flexible to changes in cell morphology and the various stages of leukaemia. Machine learning systems are more powerful than image processing systems but still require manual feature engineering. Most of these systems are only binary classification systems that cannot offer detailed leukaemia subtypes or stage classification, which limits their clinical utility.

2.2. One-deep Learning Model Systems

The recent developments proposed single deep learning models, particularly Convolutional neural networks to identify leukaemia. These models can automatically gain information about blood smear images, and they are more accurate than traditional techniques. Nevertheless, the current deep learning architectures tend to utilize a single model, which can be overfitting and has a restricted generalization capability [10]. They also have the issue of imbalance of the data sets and tend to concentrate on detection as opposed to combined diagnosis and classification of the stage. Weaknesses of the Current Systems: In general, the current systems have a low accuracy level, insufficient robustness, reliance on manual processing, and stage classification. The majority of the systems are not integrated to bring more models together to improve performance [11]. These disadvantages underscore the necessity of a smart multi model deep learning method to provide effective leukaemia diagnosis and classification of the stage.

2.3. Multiple-Models as a Deep Learning Approach

In recent years, many researchers have sought to enhance the accuracy of diagnosing leukemia through combining multiple deep learning models. Multi-model (or ensemble) learning methods merge the advantages of several different neural network architectures to increase prediction accuracy and robustness. Rather than depending on just one model, ensemble systems combine the outputs of several different Convolutional Neural Networks (CNNs) or hybrid models in order to capture different types of patterns present within medical imaging [12]. Using multiple model outputs also reduces the potential for overfitting, thus increasing generalization performance when working with small medical data sets. Multiple studies have shown that when combining different models such as ResNet, DenseNet, and Inception, the system can greatly increase performance over any single model when it comes to accurately detecting leukaemia. These methods also allow the system to identify the complex morphological characteristics of blood cells.

2.4. Comparative Evaluation of Current Techniques

A comparative evaluation of the current methods to detect leukaemia has shown that there are major differences with regard to their performance and efficiency. While traditional methods of diagnosing leukaemia manually provide accurate results, they require skilled experts and are also time-consuming. Automated processing-based image processing provides improved processing time due to automated segmentation and feature extraction; however, these systems are heavily dependent on pre-defined algorithms and depend on the quality of images used to build models using these pictures. Machine learning methods that use support vector machines (SVM), K-Nearest Neighbours (k-NN), Decision Trees, and Random Forest provide much better performance and efficiency than manual methods.

2.5. Gap in Existing Research

There has been great progress towards the automation of detecting leukaemia, but there is still work to do in the area. The vast majority of automated systems that have been created only focus on detecting leukaemia; hence do not include the staging of tumours or an analysis of the tumour

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stage severity. Most studies of automated systems for leukaemia detection use only one deep learning model; this prevents the model from learning the many different morphological features for all of the blood cell images within the dataset. All of these issues highlight the need for a multi-model intelligent deep learning framework that brings together multiple neural networks to increase the accuracy and reliability of an automated system for staging and classifying leukaemia.

2.6. Utilising Transfer Learning for Enhanced Leukaemia Detection

There has been an increasing trend in the use of transfer learning for tackling the problem of improved accuracy of detecting leukaemia due to scarce availability of extensive medical datasets. With the advent of transfer learning it has been possible to use existing deep learning models (which have been pre-trained on large datasets containing millions of images) and their features may be removed from layers of the model and fine-tuned to be used for medical image analysis of leukaemia. Commonly used models for leukaemia classification are VGG16, ResNet50, InceptionV3 and DenseNet, which have been used for leukaemia detection. When the models are used in this manner, they automatically extract high level features from images and thereby remove the need to train on large amounts of training data from the medical domain. Transfer learning has improved classification accuracy and decreased training time significantly when compared to using these models trained from scratch. However, transfer learning models depend on quality of medical datasets and may require fine-tuning to achieve optimal results.

2.7. Using Image Segmentation Techniques to Detect Leukaemia

Image Segmentation is a key technique for identifying leukaemia cells in images of blood smear slides under the microscope. A variety of segmentation techniques have been applied to isolate white blood cells and their nuclei by removing superfluous images. Generally, common techniques used for segmenting WBCs include watershed segmentation, clustering algorithms, region growing and morphological operations. Accurate segmentation is essential for capturing meaningful features that can be used to differentiate between normal and abnormal WBCs. Numerous studies demonstrate the application of traditional image processing methods together with machine learning processes; however, most of the traditional and machine learning techniques applied are used primarily for preprocessing (enhancing, segmenting, and extracting features from) images, as opposed to being the techniques used to perform final classifications. In the last few years, there has been a growing emphasis on ensemble learning and multi-model deep learning architectures, which consist of the integration of many different individual trained models to increase performance. These approaches enhance prediction of reliability, robustness, and overall diagnostic accuracy, making them highly suitable for medical image analysis and automated leukemia detection systems.

Table.1 Analysis Of The Techniques Used

Sl. No	Method / Technique / Process	No. of Times Used	References
1	CNN (Convolutional Neural Network)	6	[9], [10], [11], [12], [4], [5]
2	Transfer Learning (ResNet, VGG, MobileNet)	3	[9], [10], [11]
3	Deep Learning Based Classification	5	[9], [10], [11], [12], [4]
4	Feature Extraction & Image Processing	3	[10], [11], [12]
5	U-Net Segmentation	2	[4], [12]
6	Machine Learning (SVM / Traditional ML)	2	[11], [12]
7	Medical Image Analysis Techniques	4	[4], [5], [9], [11]
8	Epidemiological and Clinical Study	3	[1], [6], [7]
9	Leukaemia Classification & Diagnosis	4	[3], [8], [10], [12]
10	Hybrid Deep Learning Models	2	[9], [12]

2.8. Objectives

The primary goal of the project An Intelligent Multi-Model Deep Learning Approach to Accurate Leukaemia Diagnosis and Stage Classification:

- Develop an automated leukaemia detection system.
- Preprocess microscopic blood smear images.
- Improve accuracy using multi-model/ensemble techniques.
- Classify different leukaemia types or stages.

3. Comparison Of Various Survey Papers

Table. 2 Comparison of some survey papers on various criteria, including publication year, disease and the accuracy of technique/method/process applied, among other factors.

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Table I presents a comparative analysis of several survey papers related to leukaemia detection and classification. The comparison is performed based on various parameters such as publication year, disease type, techniques used, accuracy achieved, and datasets utilized. This comparison helps in understanding the progress made in the field and highlights the effectiveness of different computational approaches used for leukaemia diagnosis.

4. Conclusion

In this paper, the review of different research works involving the detection and classification of Leukemia through contemporary computational methods has been conducted. It has been demonstrated in the literature survey. The first step in the leukemia detection process was the use of traditional methods. Though these methods aided in the detection of the abnormal blood cells, they necessitated a manual extraction of features as well as lacked accuracy and efficiency. As Deep Learning has been developed, more effective medical image analysis systems have been created by researchers. Convolutional Neural Networks can be automatically trained to identify the key features of microscopic images of blood cells and can give a very high degree of precision in their classification. Such models minimize the input of human effort and enhance the accuracy of diagnosis.

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Table. 2 Comparison of some survey papers on various criteria, including publication year, disease and the accuracy of technique/method/process applied, among other factors.

S. No	Year	Disease	Accuracy	Method/Technique/Process	Dataset
1	2024	Acute Leukemia	98.2% (B-ALL), 94.6% (AML)	ResNet-50, EverFlow AI, Flow Cytometry	241 patient FCS files
2	2024	Leukemia	99.99%	Optimized CNN (OCNN) with fuzzy logic	C-NMC Leukemia dataset
3	2024	Acute Leukemia	99.3%	Ensemble model (EfficientNetB7 + MobileNetV3Large)	ALL-IDB1, ALL-IDB2
4	2024	Leukemia	94.3%	CNN + Transfer Learning (ResNet50, MobileNetV2)	C-NMC 2019 dataset
5	2024	Acute Leukemia	92.62%	VGG19, ResNet50, ResNet101	C-NMC ALL Challenge
6	2024	Leukemia	91.63%	Ensemble (InceptionResNetV2, DenseNet121, VGG16) + SVM	C-NMC dataset
7	2023	Leukemia	97.5%	CNN + Image Segmentation	ALL-IDB dataset
8	2023	Blood Cancer	96.8%	ResNet50 Transfer Learning	Kaggle Leukemia dataset
9	2023	Leukemia	98.1%	DenseNet Deep Learning Model	ALL-IDB dataset
10	2023	Acute Leukemia	97.2%	EfficientNetB4 CNN Model	C-NMC 2019

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11	2022	Leukemia	95.9%	MobileNetV2 CNN	ALL-IDB dataset
12	2022	Leukemia	96.4%	CNN + Feature Extraction	Blood Cell Images dataset
13	2022	Acute Leukemia	94.7%	VGG16 Transfer Learning	ALL-IDB2
14	2022	Leukemia	97.8%	Hybrid CNN Model	Kaggle Blood Cancer dataset
15	2021	Leukemia	95.3%	CNN + Image Processing	ALL-IDB dataset
16	2021	Leukemia	96.1%	Deep CNN Architecture	C-NMC dataset
17	2021	Blood Cancer	94.6%	Machine Learning (SVM + Feature Extraction)	Leukemia image dataset
18	2020	Leukemia	93.8%	AlexNet CNN Model	Blood smear dataset
19	2020	Leukemia	95.7%	ResNet CNN Model	ALL-IDB dataset
20	2019	Leukemia	92.4%	Traditional ML (KNN + SVM)	Microscopic Blood Cell dataset