Rev. Roum. Sci. Techn.– Électrotechn. et Énerg.
Vol. **70**, *3*, pp. 415–420, Bucarest, 2025

EARLY IDENTIFICATION OF BLOOD CANCER THROUGH AUTOMATED ANOMALY DETECTION WITH A CONVOLUTIONAL NEURAL NETWORK

RAJI VARADHAN[1], RAJENDRAN ELUMALAI PARASURAMAN [2]

Keywords: Chronic lymphocytic leukemia (CLL); Deeper with convolutions neural network (DCNN); Acute myeloid leukemia (AML); Acute lymphoblastic leukemia (ALL); Chronic myeloid leukemia (CML).

Diagnosing and assessing blood cancer requires significant time and effort due to its complexity. Improving the accuracy of information acquired through manual analysis techniques largely depends on automation tools and models. Research is advancing with early detection techniques for examining the features of human blood cells. At this point, researchers have developed deeper convolutional neural network (CNN)-based learning models, primarily utilizing hybrid ensemble DCNN approaches. With accuracy rates exceeding 99 %, this deep learning technology significantly enhances the ability to monitor the progression of blood cancer with precision. Therefore, using progressive technology to offer remedies in clinical diagnosis has become easier. The information obtained from this research, when compared with previous studies using LDSVM, demonstrates the potential to provide a better solution.

1. INTRODUCTION

Due to India's huge population, infectious diseases can spread more easily in such conditions. Alongside this, there has been a rise in cases of leukemia, a form of blood cancer. Daily diagnoses of this specific type of blood cancer are increasing, and this trend is expected to persist. This discourse will examine the intrinsic risks, manifestations, and therapeutic alternatives related to leukemia. Leukemia is a form of hematologic malignancy that impacts humans. This hematological malignancy profoundly affects two specific regions of the body: the bone marrow and the circulatory system. One of its distinguishing characteristics is the abnormal overproduction of white blood cells. Leukemia can manifest in two primary forms: In humans, if the condition is acute leukemia, it can spread rapidly throughout the body.

On the other hand, chronic leukemia sometimes spreads more slowly in humans. Both types are highly significant. Leukemia has several standard forms, including acute lymphoblastic leukemia (ALL), chronic lymphocytic leukemia (CLL), acute myeloid leukemia (AML), and chronic myeloid leukemia (CML). [15,16]. Additionally, there are other less common varieties of leukaemia. Lymphoma is a type of cancer that originates in the lymphatic system, which comprises lymph nodes, the thymus, and the spleen. Lymphoma is a broad classification used to describe cancers that affect the lymphatic system. The presence of Reed-Sternberg cells in the lymph nodes is a defining characteristic of Hodgkin's lymphoma (HL). Lymphoma typically originates in a lymph node or lymphatic tissue. Conversely, non-Hodgkin's lymphoma (NHL) comprises a range of lymphomas, each characterized by unique behaviors and therapeutic needs. NHL is a broad category that includes many subtypes.

Multiple myeloma is a malignancy that originates from plasma cells, a type of white blood cell responsible for producing antibodies. In myeloma, the aberrant plasma cells in the bone marrow proliferate excessively and infiltrate the bloodstream, impairing normal blood cell production. Additionally, these cancerous cells can damage bones and other tissues. The various types of myelomas are illustrated in a diagram. Doctors provide a wide range of treatments for this condition, as it is a significant contributor to the development of blood disorders. However, there are multiple causes for blood cancer, including genetic abnormalities, exposure to certain chemicals or radiation, or specific viral infections. Despite this, the exact causes of blood cancer remain unclear [18]. The diagnosis of hematologic malignancies relies on multiple symptoms, such as fatigue, unexplained weight loss, recurrent infections, lymphadenopathy, and increased susceptibility to bruising or bleeding. The specific symptoms depend on the subtype of the disease. Treatments for blood cancer include chemotherapy, radiation therapy, targeted therapy, immunotherapy, stem cell transplantation, and, in some cases, surgery. The choice of treatment depends on factors such as the type and stage of cancer, the patient's overall health, and specific characteristics of the disease. Blood cancer comprises numerous subtypes, each with unique characteristics.

Therefore, a diagnosis cannot be made based solely on symptoms; they serve as a guide for further investigation. Common treatments include chemotherapy, radiation therapy, targeted therapy, immunotherapy, and stem cell transplantation. Hematologic malignancies can affect both children and adults, though certain types are more prevalent in specific age groups. AML: This is a rapidly progressing form of leukemia that affects myeloid cells and can occur in both children and adults. CLL: A slow-progressing leukemia that primarily affects B-cell lymphocytes. CML: This type is characterized by the presence of the Philadelphia chromosome, which leads to the overproduction of abnormal white blood cells. It typically begins in a chronic phase but can progress to a more aggressive stage over time [15,16].

The distinguishing characteristic of HL is the presence of Reed-Sternberg cells within the lymph nodes. This condition is generally curable, especially in its early stages, and includes several subgroups. In contrast, NHL is a broad category of lymphomas that do not involve Reed-Sternberg cells. NHL serves as an umbrella term encompassing a wide range of lymphomas, each with distinct behaviors and treatment approaches [17]. Multiple myeloma is a malignancy of plasma cells, a type of white blood cell, characterized by the production of abnormal proteins that

[1] SKP Engineering College, Tiruvannamalai, Tamil Nadu, India.
E mails: raji.vpm@skpec.in, rajendran_electro@skpec.in

DOI: 10.59277/RRST-EE.2025.70.3.21

can damage bones and other organs. Another related condition is Myelodysplastic Syndromes (MDS), a group of disorders in which the bone marrow fails to produce an adequate number of healthy blood cells.

In some cases, MDS can progress to acute leukemia. Myeloproliferative Neoplasms (MPNs) are a group of disorders defined by the excessive production of one or more types of blood cells by the bone marrow. Prominent examples include primary myelofibrosis, polycythemia vera, and essential thrombocythemia. Monoclonal gammopathy of undetermined significance (MGUS) is a condition affecting plasma cells, characterized by the presence of an abnormal protein in the blood. Although MGUS typically remains asymptomatic, it can be detected through blood tests. Another rare condition is Waldenström macroglobulinemia, which is characterized by the overproduction of a specific antibody [19].

In the following sections of this paper, we will explore the remaining aspects of this inquiry in greater detail. Section 1 provides an analysis of the document. Section 2 examines advancements documented in relevant research publications and identifies key findings. Section 3 investigates the foundational assumptions of our research. Section 4 outlines the data sources and methodology used to develop our solution. Finally, section 5 presents the conclusions and the solution derived from our study.

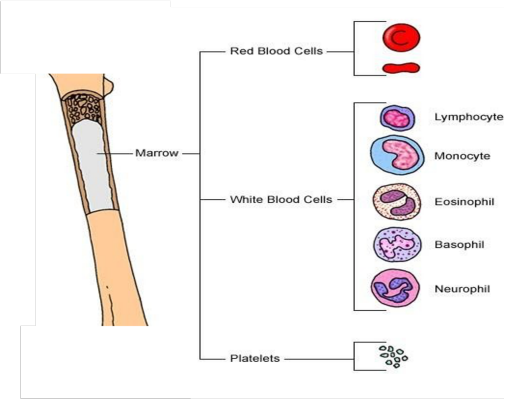

Fig. 1 – Bone marrow is a vital tissue within bones.

2. LITERATURE SURVEY

This literature review examines the application of deep learning, image processing, and nanosensor technologies for the automatic detection, classification, and early diagnosis of blood cancer, specifically leukemia, employing various techniques [1]. These methodologies primarily focus on deep learning, image processing, and nanosensor technologies [14]. The review emphasizes the role of leukocytes in blood cancer, highlighting how deep learning enhances accuracy and minimizes errors associated with manual interventions. Techniques such as the K-Means algorithm and microscopic imaging are employed to identify leukemia early and effectively, enabling prompt and cost-effective diagnosis [2,3]. Additionally, mobile nanosensors have been shown to detect cancer in blood vessels at an early stage, addressing the challenge of low biomarker concentrations in conventional tests [20].

The process of disease prediction and addressing machine-related complexities is a crucial aspect of this research. This review examines the selection of learning models and the inherent challenges associated with them. While the primary focus is on Parkinson's disease, it underscores the importance of stable wavelet transform filters for analyzing MRI images and EEG signals in disease detection. Another study introduces the DRI-FH model, a deep learning framework designed to detect tricuspid regurgitation (TR) in its early stages. Feature extraction methods and preprocessing techniques, including color-level co-occurrence matrices (CLCM) and gray-level co-occurrence matrices (GLCM), are emphasized in this research as crucial components. These methods can be adapted to improve the classification of cancer cells in blood smear images [21]. Finally, Table 1 provides a summary of the various age groups and the types of blood cancers that can affect each group.

Table 1

The types of blood cancers and general age groups.

Type of Blood Cancer	Age Groups Affected
Acute Lymphoblastic Leukemia (ALL)	Children, Adolescents, Young Adults
Hodgkin Lymphoma	Children, Adolescents, Young Adults
Non-Hodgkin Lymphoma	Children, Adolescents, Young Adults, Middle-Aged, Elderly
Acute Myeloid Leukemia (AML)	Young Adults, Middle-Aged, Elderly
Chronic Lymphocytic Leukemia (CLL)	Middle-Aged, Elderly
Myelo proliferative Neoplasms (MPNs)	Middle-Aged
Myelo dysplastic Syndromes (MDS)	Middle-Aged
Multiple Myeloma	Elderly

This article's goal is to give a thorough analysis of DL and traditional machine learning (TML) algorithms for WBC classification in blood smear pictures. This emphasizes the need for the development of convolutional neural network (CNN) models in this area [5,11,12]. For efficient real-time retrieval, the researcher proposes the MEDI-NET approach for medical data. This method facilitates the simultaneous extraction of information from large datasets, aiding in real-time data analysis. According to our research, this method is effective for automatically detecting cancer, as it enables the extraction of valuable data from data-rich environments, such as medical information systems [22]. The proposed approach employs the CMYK-moment localization method and a CNN-based feature fusion technique to extract characteristics from white blood cells. The examination of attributes obtained through classification algorithms illustrates the capability of deep learning to enhance classification precision [6]. This investigation employs digital image processing techniques to explore leukemia diagnosis and its various forms [13].

This work aims to examine the use of machine learning, specifically support vector machine (SVM) classifiers, in evaluating blood smear images to distinguish between healthy individuals and those diagnosed with leukemia [7]. The goal of this research is to develop a program that can accurately diagnose and classify various types of leukemia using microscopic images of blood cells. When classifying ALL and AML, several processing stages contribute to the overall classification process [8]. These stages include pre-processing, segmentation, and feature extraction. The

research employs blood microscopy images to explore various methods for diagnosing and classifying leukemia. This article examines the impact of leukemia on the bone marrow and the challenges and techniques involved in analyzing and categorizing the various types of leukemia. Table 2 delineates the similarities and differences among three fundamental categories of hematologic malignancies: leukemia, lymphoma (encompassing both HL and NHL), and myeloma. CNNs are a type of neural network widely used in image analysis tasks because they can learn hierarchical features from images autonomously [11, 12].

Table 2

Compares and contrasts the main types of blood cancers

Aspect	Lymphoma	Leukemia	Myeloma
Definition	Cancer of lymphatic system	Cancer of blood cells, affects bone marrow	Cancer of plasma cells in bone marrow
Main Subtypes	Hodgkin, Non-Hodgkin	ALL, AML, CLL, CML	Multiple Myeloma
Progression	Gradual progression	Acute or Chronic	Slow progression, can be chronic
Common Age Group	Affects all age groups	Varies by subtype	More common in older adults
Affected Cells	Lymphocytes	Blood cells (lymphocytes, myeloid cells)	Plasma cells
Treatment	Chemotherapy, radiation, immunotherapy	Chemotherapy, targeted therapy, transplant	Chemotherapy, targeted therapy, transplant
Prognosis	Depends on type and stage	Depends on subtype and stage	Depends on stage and patient factors

The BH2Mnet network, designed for brain tumor detection using MEG (Magnetoencephalography) and PET (Positron Emission Tomography) scans within a hybrid hexagonal mobile framework, primarily employs these imaging techniques for brain activity and metabolic imaging rather than cellular-level imaging. This study identifies key challenges in deep learning, such as noise removal, segmentation, and analysis, which impact the enhancement of image datasets during training. The quality of image datasets can be improved by applying techniques such as adaptive bilateral filtering and advanced segmentation algorithms, including the Kapur-Otsu thresholding method. Additionally, these techniques can be adapted for leukemia detection from blood smear images, offering a versatile solution to medical imaging challenges [23]. The ensemble LDSVM model is proposed for the classification of leukemia cancer. The researchers utilized the GSE9476 dataset from Kaggle for their study. To evaluate performance, they use k-fold cross-validation to enhance its effectiveness.

Additionally, for assessment in machine learning, evaluation parameters include random forest, gradient boosting machine, decision tree, naive bayes, linear regression, and SVM. In contrast to your research, this study employs advanced learning techniques to achieve highly accurate results in a minimal amount of time. Furthermore, the comparison between their study and ours is demonstrated using metrics such as precision, accuracy, recall, and F1-score [24].

CNNs have demonstrated exceptional performance on a variety of visual tasks, including image classification, object recognition, and scene segmentation. Researchers have found CNNs to be highly effective in diverse applications, including classifying different types of blood cells and detecting abnormalities in blood cancer images [9]. In addition to CNNs, alternative deep learning architectures, such as long short-term memory (LSTM) networks and recurrent neural networks (RNNs), can be used to complement CNNs for sequential data processing. For example, these designs are particularly useful for analyzing time-series images [10]. Sequential data processing can benefit significantly from these architectures.

3. PROPOSED SYSTEM

Convolutional Neural Networks (CNNs) are combined with hybrid neural networks and deep learning methods to create a hybrid architecture. In this study, we observed that traditional image classification methods sometimes produce errors. To address these issues and improve accuracy, we propose a novel hybrid learning approach. This approach combines deep learning and machine learning techniques, with the primary objective of extracting the most significant features from images and accurately classifying them.

Additionally, this method effectively resolves challenges related to feature selection and ensures precise and clear image classification. The goal of this combined approach is to achieve improved performance across the board, particularly in image recognition and analysis. We optimize directed convolutional neural networks, a subset of deep neural networks, to process images and other grid-like data. Convolutional layers provide an efficient mechanism for learning features from input data, excelling at feature extraction and pattern identification. CNNs (Convolutional Neural Networks) are particularly effective in applications such as image classification, object detection, and image segmentation. Due to their multiple hidden layers, they process data through various network structures, enabling them to learn and extract information in a highly detailed and nuanced manner, which is then used for testing and analysis. This technique, known as deep learning, forms the foundation of our proposed hybrid architecture.

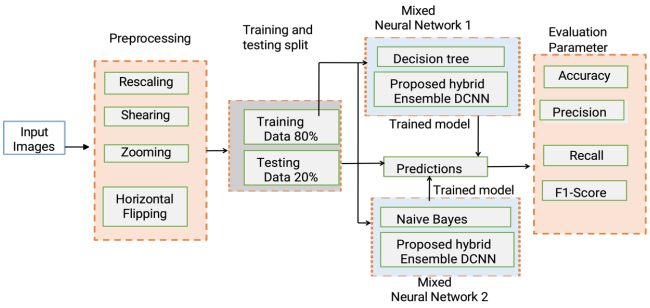

Fig. 2 – One method for detecting blood cancer using a mixed neural network (MNN).

Image classification involves accurately categorizing images based on standard features identified across multiple images. However, challenges arise when classifying images with complex characteristics and fewer distinctive features, especially when the common features are either excessive or insufficient. To address this issue, a hybrid approach can be used to identify which specific features are insufficient and replace them with alternative representative features. By leveraging a deep learning model, this method groups

the features and suggests additional important ones. Our new hybrid learning approach, combined with an ensemble technique, ensures that the classification achieves up to 99% accuracy.

The Mixed Neural Network (MNN) method offers several benefits, as illustrated in Fig. 2, particularly in detecting blood cancer. By incorporating deep learning and convolutional neural networks (CNNs) into our research, MNN identifies complex image patterns and generates accurate solutions from them, resulting in highly precise diagnoses. This method simplifies the extraction of complex features from images used in blood cancer research, leading to comprehensive and accurate diagnoses.

MNN's ability to recognize complex variations and patterns enables the detection of all relevant information related to blood cancer at an early stage, thereby improving treatment outcomes. Furthermore, its multi-level analysis reduces false positives and increases reliability. MNN's personalization capabilities and contributions to research enhance the accuracy of blood cancer diagnosis, and the solutions it provides improve patient care. A mixed neural network combines the strengths of CNNs and deep learning. It captures spatial features in blood cancer images through CNNs, while the term 'hybrid' refers to the combination of these techniques, leveraging their complementary strengths to achieve improved performance and accuracy. Implementing machine learning concepts in the analysis of blood cancer images involves fundamental steps such as data collection, preprocessing, model development, training, and evaluation.

4. RESULT AND ANALYSIS

Here, we discuss the functioning of the deep convolutional neural network model we proposed for the detection of leukemia, a type of blood cancer. For this study, as shown in Figure 3, the dataset is divided into 80% for training data and 20% for testing data. The dataset consists of blood cancer images, which are used as input to develop and train two distinct hybrid neural networks. Mixed Neural Network 1 consists of two models: a decision tree model and a hybrid deeper convolutional neural network (DCNN). The decision tree model classifies the data by generating rules that help identify whether a cell is cancerous. Meanwhile, the deeper DCNN processes images through layers, including convolutional, pooling, and fully connected layers, automatically extracting key features such as structure and color intensity, thereby enhancing classification accuracy. Predictions from these models are combined using ensemble techniques to improve performance. Similarly, Mixed Neural Network 2 comprises a Naive Bayes classifier and another hybrid deeper CNN. The Naive Bayes classifier, based on Bayes' theorem, is a probabilistic model that generates predictions to determine whether each blood cell is affected by cancer or not. At the same time, the deep DCNN (Deep Convolutional Neural Network) processes the input through multiple layers to extract detailed features and stabilize the learning process. The outputs from both models are combined using ensemble methods to enhance the precision of the predictions. The final forecasts from both hybrid networks are generated using an ensemble approach, ensuring robustness. This approach demonstrates improved performance and accuracy on the test data, successfully identifying blood cancer cells, as shown in Fig. 4.

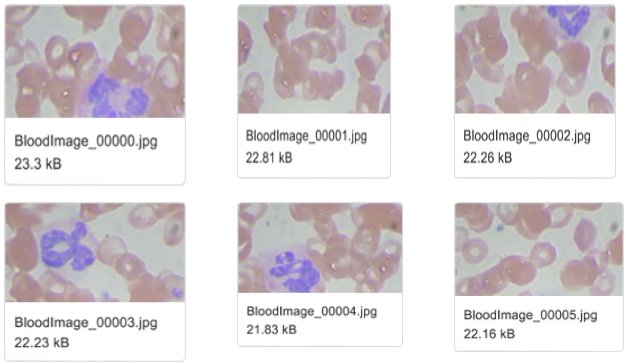

Fig. 3 – Normal Dataset.

Fig. 4 – Blood Cancer Dataset.

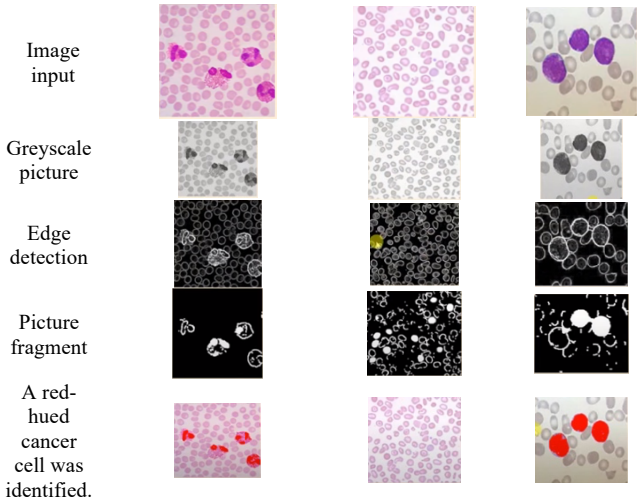

Fig. 5 – Using an MNN model to identify possible cancer cells in the blood.

The Kaggle platform provides medical image data, including datasets related to blood cancer. The data is preprocessed using operations such as zooming, shearing, flipping, and rescaling. For instance, a horizontal flip of an image causes a pixel at position (x, y) to shift to (width - x - 1, y) in the new image. Fig. 3 and Fig. 4 display normal and blood cancer images from the dataset, respectively. The Mixed Neural Network (MNN) method is utilized for blood cancer diagnosis, relying on input images, grayscale conversion, edge detection, segmented images, and the recognition of cancer cells. Grayscale conversion simplifies data analysis by reducing the complexity of the image data. During testing, two trained models classify the test data, and an Ensemble Voting Classifier makes the final prediction, as shown in Fig. 5. This classifier improves the accuracy and reliability of blood cancer detection by combining predictions from multiple instances of the MNN model. By aggregating outcomes from different MNN models, the ensemble voting

classifier produces a consensus prediction, reducing the risk of false positives or false negatives.

We propose using a hybrid deeper convolutional neural network model for the detection of leukemia, a type of blood cancer. The performance of this model is evaluated based on several parameters, including accuracy, precision, recall, and F1-score, as part of the performance evaluation process. These metrics are essential for the analysis as they demonstrate how effectively the proposed model classifies blood cancer cells with high accuracy and reliability.

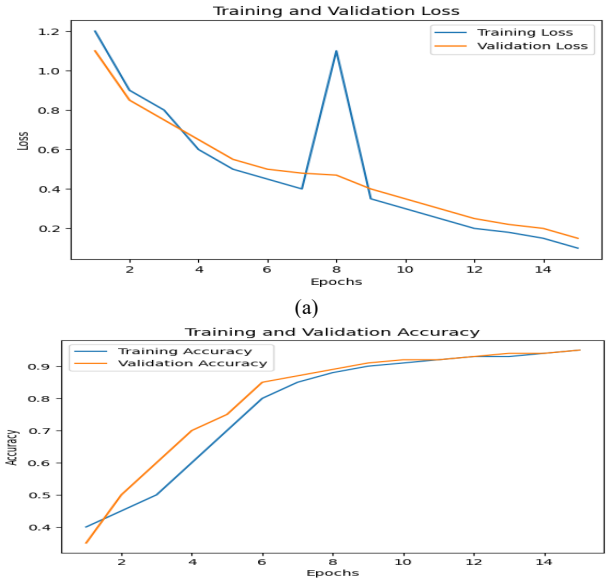

Fig. 6 – (a) and (b) illustrate the accuracy and loss of normal blood cells during training and validation, respectively.

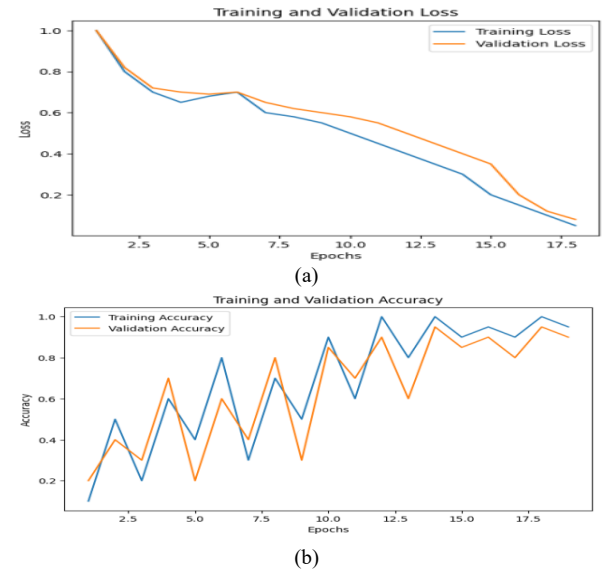

Fig. 7 – (a) Training and validation accuracy in blood cancer, and (b) Learning and validation loss in blood cancer.

Accuracy refers to the proportion of correctly predicted instances relative to the total number of predictions in our study. Within the context of the dataset, high accuracy indicates the model's ability to distinguish between normal and cancerous cells effectively. Additionally, precision is calculated as the ratio of true positives to the sum of true positives and false positives. It measures the proportion of correctly identified cancer cells out of the total number of cells predicted as cancerous. A high precision value indicates that most cells classified as cancerous are indeed cancerous, thereby minimizing false positives. Recall, also known as sensitivity or the true positive rate, measures the percentage of actual cancer cells correctly identified by the model. It ensures that the majority of true cancer cells are detected, reducing the likelihood of missing cells affected by leukemia-related conditions. The F1 score, which is the harmonic mean of precision and recall, provides a balanced metric. This is particularly useful in scenarios where both false positives and false negatives carry significant consequences. It ensures a comprehensive evaluation of the model's performance in distinguishing between normal and cancerous cells. A high F1 score, as shown in Table 3, indicates that the system is reliable and consistent in medical diagnosis. This is especially critical, as failing to identify cancer cells can have serious implications.

To evaluate the model's performance, we used cross-validation within the context of the test dataset. We independently tested two hybrid models and combined their results using an ensemble method to arrive at the final prediction. This ensemble approach further improved the overall precision and robustness of the model, making it an excellent method for accurate leukemia detection.

Table 3

Comparative analysis of proposed work

Methods	Accuracy	Precision	Recall	F1 Score
Naïve bayes	0.979	0.965	0.957	0.98
Decision tree	0.856	0.91	0.87	0.86
LDSVM [24]	0.968	0.967	0.96	0.93
Proposed approach Ensemble DCNN	0.99	0.989	0.987	0.98

This ensemble method improves the accuracy and robustness of blood cancer case diagnoses from medical pictures by combining the best features of several MNN models. We use the results of this prediction in Figs. 6 and 7 to determine whether the given picture exhibits signs of blood cancer or not. Helping clinicians comprehend and use CNNs for blood cancer image analysis requires open communication, honesty, and addressing concerns. Better patient care will result from increased confidence in and use of AI by healthcare providers and other AI-powered tools.

5. CONCLUSION

Blood cancer causes a significant number of cancer-related deaths. Recent studies have demonstrated promising results in identifying blood cancer through deep learning approaches that utilize transfer learning techniques. However, researchers continue to explore ways to enhance deep learning systems. To aid in the diagnosis of blood cancer using ultra-small blood samples taken from patients, this study introduces an improved deep learning model based on a DCNN architecture. We have validated the proposed model by comparing it using commonly available datasets. When compared to traditional deep learning benchmarks, the results have been achieved in a reliable and convincing manner.

CREDIT AUTHORSHIP CONTRIBUTION

Rajendran Elumalai Parasuraman: Contributed equally to the current study at every level, from problem formulation to final results and resolution.

Raji Varadhan: Contributed equally to the current study at every level, from problem formulation to final results and resolution.

Received on 4 February 2025

REFERENCES

1. D. Kumar, *Automatic detection of white blood cancer from bone marrow microscopic images using convolutional neural networks*, IEEE Access, **8**, pp. 142521–142531 (2020)
2. P. Ranjitha, S. Duth. *Detection of blood cancer-leukemia using k-means algorithm*, 5th International Conference on Intelligent Computing and Control Systems (ICICCS), IEEE (2021)
3. R. Mosayebi, *Early cancer detection in blood vessels using mobile nanosensors*, IEEE transactions on nanobioscience,**8**, *2,* pp. 103–116 (2018).
4. S. Khan, *A review on traditional machine learning and deep learning models for WBCs classification in blood smear images*, IEEE Access, **9**: pp.10657–10673 (2020).
5. T.A.M. Elhassan, *Feature extraction of white blood cells using CMYK-moment localization and deep learning in acute myeloid leukemia blood smear microscopic image*, IEEE Access, **10**, pp.16577–16591 (2022).
6. T. Dharani, S. Hariprasath, *Diagnosis of leukemia and its types using digital image processing techniques*, 3rd International Conference on Communication and Electronics Systems (ICCES), IEEE, (2018)
7. R. Sigit, M.M. Bachtiar, M.I. Fikri, *Identification of leukemia diseases based on microscopic human blood cells using image processing*. International Conference on Applied Engineering (ICAE), IEEE, (2018)
8. V.J. Ramya, S. Lakshmi, *A methodical review of diagnosis and classification of leukemia using blood microscopic images*, International Conference on Communication and Signal Processing (ICCSP), IEEE, (2019)
9. T. Kattenborn, *Review on Convolutional Neural Networks (CNN) in vegetation remote sensing*, ISPRS Journal of Photogrammetry and Remote Sensing, **173,** pp.24-49, (2021)
10. O. Calin, *Deep learning architectures*, New York City, Springer International Publishing, (2020)
11. M.S. Alim, S.D. Bappon, S.M. Sabuj, M.J. Islam, M..M Tarek, M.S. Azam, M.M. Islam, *Integrating convolutional neural networks for microscopic image analysis in acute lymphoblastic leukemia classification: A deep learning approach for enhanced diagnostic precision*, Systems and Soft Computing (2024).
12. N. Alshdaifat, H.A. Owida, Z. Mustafa, A. Aburomman, S. Abuowaida, A. Ibrahim, W. Alsharafat, *Automated blood cancer detection models based on EfficientNet-B3 architecture and transfer learning*, Indonesian Journal of Electrical Engineering and Computer Science,**36**, *3* (2024).
13. K. Lalithkumar, M.A. Priyanga, S. Sandhya, M. Karthiga, *CapsENet: Deep Learning based Acute Lymphoblastic Leukemia Detection Approach*, 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC), pp. 1577–1584, IEEE, (2024)
14. S.A. Preanto, M.T. Ahad, Y.R. Emon, S. Mustofa, M. Alamin, *A study on deep feature extraction to detect and classify Acute Lymphoblastic Leukemia* (ALL), arXiv preprint arXiv:2409.06687 (2024).
15. M. Iswarya, *Detection of Leukemia using machine learning*, International Conference on Applied Artificial Intelligence and Computing (ICAAIC), pp. 466–470, IEEE (2022).
16. A. Shridhar, P.S. Baghel, R. Mahobia, O. Bhargava, S. Totade, *Study of prevalence of acute leukemia*, International Journal of Health Sciences, **6**, *S8*, pp.6995–7001 (2023).
17. P.D. Saragea*, A Comprehensive Overview of Malignant Lymphomas: Classification, Epidemiology, and Clinical Insights* (2024)
18. B.T. Hill, *Etiology of cancer, Clinical Ophthalmic Oncology: Basic Principles*, pp.11–17, (2019)
19. Q. Lu, D. Yang, H. Li, H, T. Niu, A. Tong, *Multiple myeloma: signaling pathways and targeted therapy*, Molecular Biomedicine, **5**, *1*, pp. 25 (2024).
20. A. Ramaiah, P.D. Balasubramanian, A. Appathurai, M. Narayanaperumal, *Detection of Parkinson's disease via Clifford gradient-based recurrent neural network using multi-dimensional data,* Rev. Roum. Sci. Techn. – Électrotechn. Et Énerg., **69**, *1*, pp.103–108 (2024).
21. M.B. Priya, C. Ramakrishnan, S. Karthik, *Fetal 3D-Echo classification and segmentation using color and textural features for tr detection*, Rev. Roum. Sci. Techn. – Électrotechn. Et Énerg., **69**, *1*, pp.115–120 (2024).
22. S. Palanisamy,T. Ramasamy, *MEDI-NET: cloud-based framework for medical data retrieval system using deep learning*, Rev. Roum. Sci. Techn. – Électrotechn. Et Énerg., **69**, *2*, pp.255–260, (2024)
23. A. Appathurai, A.S.I. Tinu, M., Narayanaperumal, M., *MEG and PET images-based brain tumor detection using Kapur's Otsu segmentation and Sooty optimized Mobilenet classification*, Revue Rev. Roum. Sci. Techn. – Électrotechn. Et Énerg., **69**, *3,* pp. 359–364 (2024).
24. A. Karim, A, Azhari, M. Shahroz, S. Brahim Belhaouri, K. Mustofa, *LDSVM: Leukemia cancer classification using machine learning,* Computers, Materials & Continua, **71**, *2* (2022).