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Optimized Classification of Blood Cancer Using Recurrent Neural Networks

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***Abstract* - Blood cancer remains one of the most fatal diseases, underscoring the need for early detection to improve survival rates. Traditional convolutional neural network (CNN)-based models, while effective in feature extraction, often suffer from overfitting when applied to small or imbalanced datasets, thereby reducing their predictive accuracy. To overcome this limitation, this study proposes a hybrid deep learning model that integrates bidirectional long short-term memory (BiLSTM) with MobileNet. MobileNet efficiently extracts spatial features from medical images, while BiLSTM captures long-term dependencies within the data, enhancing model robustness and generalization. This combination improves the system's ability to recognize complex patterns, resulting in more accurate blood cancer classification. By leveraging the strengths of both architectures, the proposed model mitigates overfitting, enhances predictive performance, and ensures reliable diagnosis. Experimental results demonstrate that the hybrid approach significantly outperforms conventional CNN-based models in terms of accuracy and generalization. This study highlights the potential of deep learning in medical diagnostics and offers an effective solution for improving blood cancer prediction, ultimately contributing to better clinical decision-making and improved patient outcomes.**
Keywords: **Blood Cancer, Deep Learning, BiLSTM, MobileNet, Medical Image Classification**

I. INTRODUCTION

Blood cancer**,** or hematologic malignancy, affects the blood, bone marrow, and lymphatic system, disrupting immune function, oxygen transport, and clotting. The three main types-leukemia, lymphoma, and myeloma-result in abnormal white blood cell growth, impairing immunity. Leukemia originates in the bone marrow, lymphoma affects lymphocytes, and myeloma weakens plasma cells, leading to complications such as bone damage and kidney failure. Early detection is crucial yet challenging due to nonspecific symptoms. AI-powered diagnostic tools enhance accuracy, enabling timely treatment and improved patient outcomes.

A. Benign

Benign blood conditions are non-cancerous but may still require treatment. Some, such as leukocytosis and thrombocytosis, can mimic malignancies, making accurate diagnosis essential. Unlike cancer, these conditions do not involve uncontrolled cell growth, and many, including anemia, are manageable. Advanced diagnostic tools, including artificial intelligence and genetic testing, assist in accurate diagnosis and effective treatment planning.

B. Malignant Pre-B

Malignant Pre-B is an aggressive form of B-cell acute lymphoblastic leukemia (B-ALL), characterized by the uncontrolled proliferation of immature Pre-B cells, which disrupt normal blood cell production. Symptoms include frequent infections, anemia, easy bruising, and bone pain. Diagnosis involves blood tests, bone marrow biopsy, and genetic profiling. Treatment typically includes chemotherapy, targeted therapies, and chimeric antigen receptor (CAR) T-cell therapy.

C. Malignant Pro-B

Malignant Pro-B leukemia is a highly aggressive subtype of B-ALL, marked by the failure of immature Pro-B cells to differentiate and their uncontrolled proliferation. This subtype is associated with high-risk genetic abnormalities and severely impairs normal blood cell production. Common symptoms include persistent fever, infections, anemia, bruising, and organ enlargement.

D. Malignant Early Pre-B

Malignant early Pre-B leukemia is a severe subtype of B-ALL involving the malignant transformation of early B-cell precursors. It affects both children and adults and presents with fatigue, infections, bruising, and bone pain. The disease often leads to anemia, thrombocytopenia, and neutropenia, compromising immune function. Genetic mutations, such as the *ETV6-RUNX1* fusion, play a significant role in disease progression and treatment response.

II. RELATED WORK

W. Rahman, M. G. G. Faruque, K. Roksana, A. H. M. S. Sadi, M. M. Rahman, and M. M. Azad [1] presented a machine learning (ML) and deep learning (DL) approach for leukemia classification, involving dataset construction, CNN-based feature extraction, and ML-based classification.

Malignant cases are categorized into Early Pre-B, Pre-B, and Pro-B, with techniques such as principal component analysis (PCA), linear discriminant analysis (LDA), particle swarm optimization (PSO), and cat swarm optimization (CSO) used for feature refinement. Seven ML classifiers are applied, achieving high classification accuracy.

A. A. Althaf, K. Hemalatha, N. M. Priya, S. Aswath, and S. Jaiswal [10] explores artificial neural network (ANN)-based blood cancer diagnosis using sensor network data. Physiological parameters such as heart rate, temperature, and blood pressure are processed through ANN classifiers, achieving an accuracy of 92.1%. The study highlights the role of sensor network data in enhancing early detection and reducing diagnostic errors.

N. P. Dharani, G. Sujatha, and R. Rani [3] automated blood cancer detection method using an improved ML algorithm is proposed, integrating the ensemble method, enhanced fuzzy c-means (EFCM), and iterative morphological processing (IMP). Image segmentation and enhancement techniques focus on cancer-specific regions, improving diagnostic accuracy. This approach ensures faster, cost-effective, and precise diagnosis.

T. G. Prakash, C. L. Kumar, and M. S. Kumar [4] review the application of convolutional neural networks (CNNs) in leukemia detection. Manual microscopic examination is time-consuming and prone to human error, making AI-driven methods essential. The research analyzes benchmark datasets and compares methodologies to improve blood cancer diagnostics.

M. U. Nasir, M. F. Khan, M. A. Khan, M. Zubair, S. Abbas, M. Alharbi, and Md A. Akhtaruzzaman [5] focused on early blood cancer detection using deep learning with transfer learning techniques. Models such as AlexNet, MobileNet, and ResNet are evaluated, with AlexNet achieving an accuracy of 87.3%. The proposed approach integrates image processing with cloud-based optimization to enhance diagnostic efficiency.

III. PROPOSED SYSTEM

The proposed system integrates bidirectional long short-term memory (BiLSTM) with MobileNet to enhance blood cancer prediction by addressing overfitting issues common in traditional CNN-based models. MobileNet, a lightweight deep learning model, is employed for efficient feature extraction, capturing essential patterns in microscopic blood cell images while maintaining computational efficiency. This enables the model to process large datasets without excessive resource consumption. BiLSTM, in contrast, excels at capturing long-term dependencies in sequential data. Unlike standard LSTMs, BiLSTM processes data in both forward and backward directions, improving contextual understanding and enabling the model to learn relationships between features extracted by MobileNet. This dual mechanism enhances the model's ability to distinguish between normal and cancerous blood cells. By combining MobileNet and BiLSTM, the proposed hybrid approach improves generalization and reduces overfitting-an issue frequently encountered in deep learning models trained on limited medical datasets. Additionally, this approach improves adaptability to unseen data, increasing the reliability and robustness of blood cancer prediction. The fusion of these two models facilitates more accurate and efficient diagnosis, contributing to improved early detection and better treatment planning in hematology.

A. Data Collection

The dataset sourced from Kaggle.com includes labeled blood sample images that assist deep learning models in distinguishing between healthy and cancerous white blood cells (WBCs). Accurate labeling enhances feature extraction and classification accuracy. Exposure to diverse cell structures improves generalization, increasing the system's reliability for early blood cancer detection.

B. Pre-processing

Pre-processing optimizes the dataset for deep learning by ensuring clean and standardized input data. Blood cell images are resized for uniformity, and normalization is applied to scale pixel values, stabilizing training. Data augmentation techniques-including rotation, flipping, and scaling-enhance model robustness and reduce overfitting. Class imbalance is addressed through oversampling or under sampling to ensure fair representation of both normal and cancerous cells. These steps improve feature extraction and contribute to higher accuracy, reliability, and efficiency in blood cancer detection.

C. Feature Extraction

Feature extraction plays a crucial role in blood cancer detection, with MobileNet efficiently capturing spatial features using depthwise separable convolutions. These features, representing cell morphology, are then processed by BiLSTM to analyze sequential dependencies. This combination enhances classification accuracy and improves cancer detection performance.

D. Model Creation

The system integrates MobileNet for spatial feature extraction and BiLSTM for sequential analysis, thereby enhancing blood cancer detection. MobileNet effectively captures structural features, while BiLSTM identifies temporal patterns, improving classification accuracy. This hybrid approach increases reliability and reduces overfitting, making it suitable for medical applications.

E. Test Data

Test data is essential for evaluating the performance of the MobileNet-BiLSTM model in blood cancer detection. A separate dataset of labeled blood cell images is used to ensure an unbiased assessment. Evaluation metrics such as accuracy, precision, and F1-score are utilized to analyze classification effectiveness. Testing also helps identify model limitations, guiding future improvements to enhance reliability in real-world diagnostic settings.

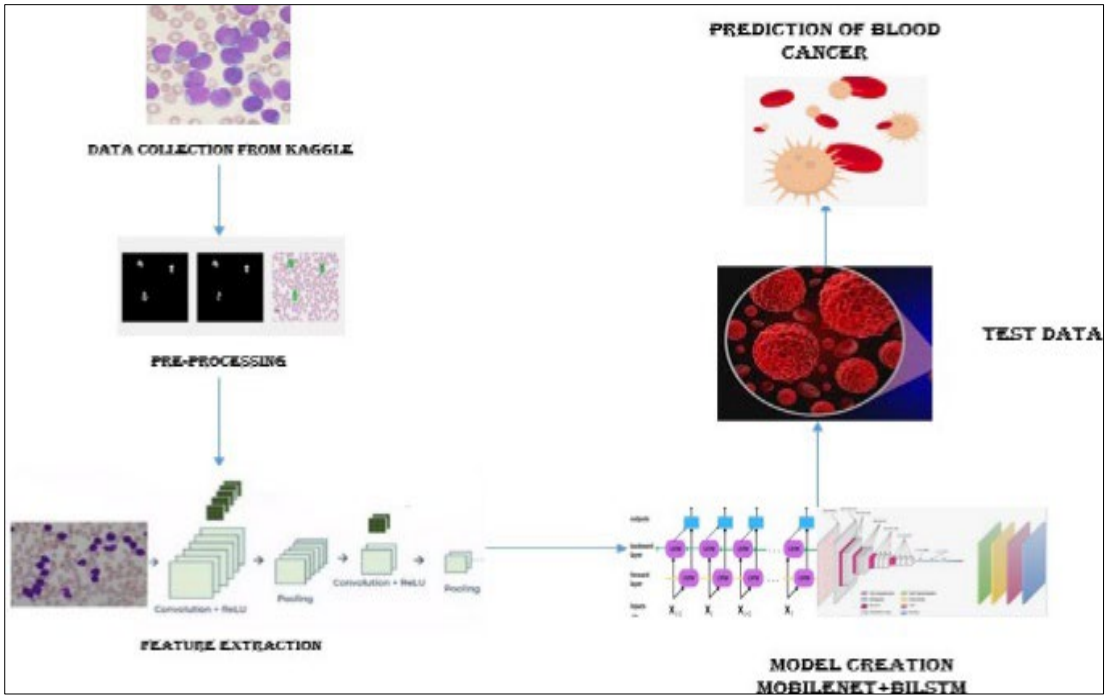

Fig.1 Workflow Diagram

F. Prediction

The proposed model classifies blood cell images by using MobileNet for feature extraction and BiLSTM for pattern recognition. It assigns probabilities to each category and selects the one with the highest probability as the prediction. Performance is evaluated using metrics such as accuracy and F1-score, ensuring reliable blood cancer detection for early diagnosis.

IV. RESULTS AND DISCUSSION

The MobileNet-BiLSTM hybrid model enhances blood cancer prediction by combining efficient feature extraction with sequential learning. MobileNet captures spatial features, while BiLSTM improves contextual understanding, thereby reducing overfitting and improving generalization. Performance metrics indicate higher accuracy and lower misclassification rates. This approach supports early diagnosis, enabling timely treatment and improved patient outcomes.

A. Accuracy

The MobileNet-BiLSTM model achieves an accuracy of 98.5%, outperforming traditional CNN-based approaches. MobileNet efficiently extracts spatial features, while BiLSTM captures sequential dependencies, significantly enhancing classification performance in blood cancer detection.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

This high accuracy is attributed to MobileNet's efficient extraction of meaningful spatial features from blood cell images. BiLSTM enhances feature learning by capturing sequential dependencies, thereby reducing misclassification and improving generalization. The model also achieves high precision and recall, ensuring reliable differentiation between normal and cancerous cells.

The proposed system's high accuracy, reduced overfitting, and improved generalization make it an effective tool for early blood cancer diagnosis. This facilitates timely and accurate detection, leading to better treatment strategies and improved patient outcomes.

B. Loss

In the proposed system, loss measures the difference between predicted and actual labels in blood cancer classification. A lower loss indicates higher prediction accuracy, whereas a higher loss reflects greater discrepancies between predictions and true values.

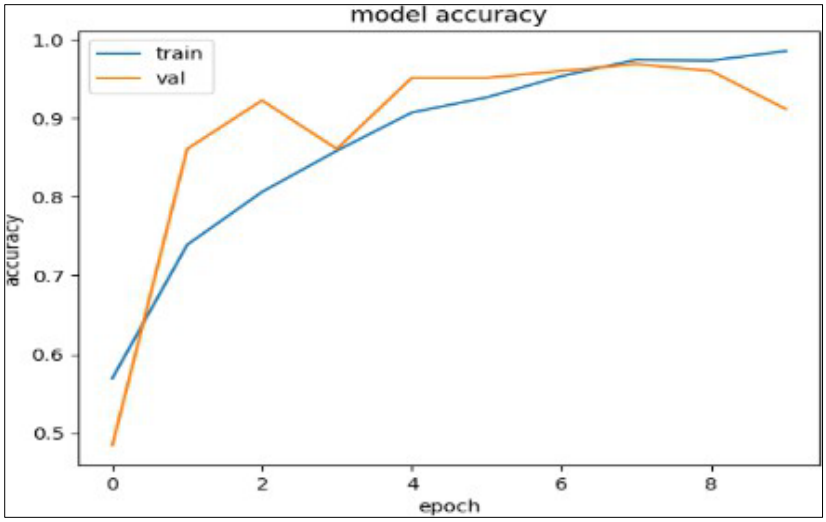

Fig.2 Model Accuracy

Cross-entropy loss is employed to evaluate classification performance, guiding model optimization to enhance accuracy and reliability.

$$L = -\sum_{i=1}^{n} \sum_{j=1}^{m} y_{ij} \, log(\hat{y}_{ij}) \qquad (2)$$

Overfitting occurs when a model memorizes the training data but fails to generalize to new, unseen samples. To mitigate this issue, the proposed system combines MobileNet for feature extraction and BiLSTM for sequential learning. Regularization techniques such as dropout and data augmentation are employed to enhance generalization by preventing overfitting and stabilizing the loss function. As training progresses, a decreasing loss value indicates improved predictive performance. However, if the loss stagnates or increases, tuning hyperparameters or modifying the model architecture may be necessary. Minimizing the loss is essential to ensure a reliable blood cancer diagnosis.

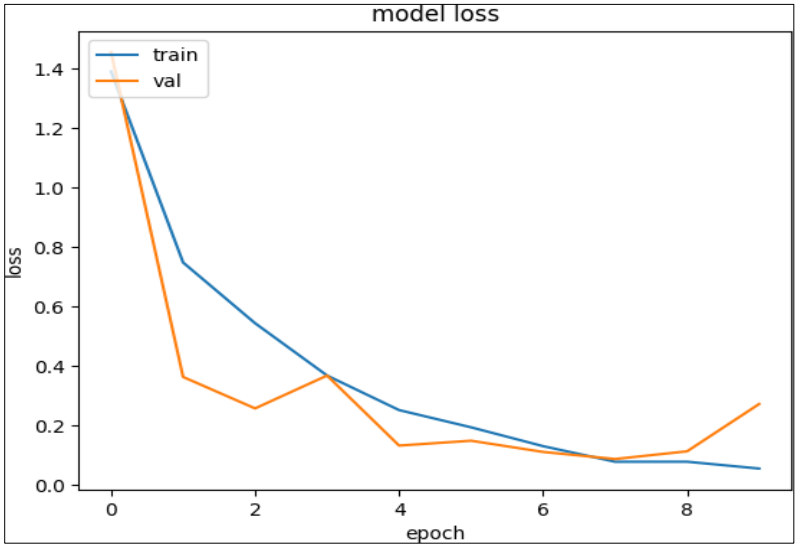

Fig.3 Model Accuracy

C. Precision

Precision in the BiLSTM-MobileNet model ensures accurate identification of cancerous blood cells while minimizing false positives. High precision is critical in medical diagnosis, as it helps prevent unnecessary treatments and reduces patient anxiety. By combining MobileNet's efficient feature extraction with BiLSTM's sequential learning capabilities, the system improves classification accuracy and reduces misclassifications.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad (3)$$

Precision minimizes false positives, ensuring accurate cancer diagnosis. MobileNet extracts key features, while BiLSTM refines patterns, thereby enhancing model reliability. Balancing precision and recall are essential for optimizing overall classification performance.

D. Recall

Recall ensures that the model correctly identifies cancerous cases, minimizing the risk of missed diagnoses. MobileNet is responsible for extracting relevant features, while BiLSTM captures temporal dependencies, improving the detection of subtle variations in blood cell morphology.

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

A high recall ensures minimal missed cancer cases, enhancing the system's reliability for early diagnosis. The model effectively balances precision and recall, thereby reducing both false negatives and false positives to improve overall diagnostic accuracy.

E. F1-Score

The F1-score provides a balance between precision and recall, making it particularly useful for imbalanced datasets. It considers both false positives and false negatives, with a higher F1-score indicating better overall classification performance.

$$F1\ Score = 2 \times \frac{Precision\ .\ Recall}{Precision+Recall} \quad (5)$$

The F1-score is crucial in medical diagnostics, such as blood cancer classification, as it balances precision and recall to minimize both false positives and false negatives, thereby reducing misdiagnoses and improving reliability.

V. CONCLUSION

Blood cancer remains a life-threatening disease, necessitating early and accurate diagnosis to improve patient survival rates. Traditional CNN-based models, while effective for feature extraction, often suffer from overfitting and poor generalization, particularly when trained on limited or imbalanced medical datasets. To address these challenges, this study introduces a hybrid deep learning model that integrates MobileNet for efficient feature extraction and BiLSTM for capturing long-term dependencies within the data. This combination enhances the model's ability to recognize complex patterns in blood cell images, resulting in improved classification accuracy.

Experimental results demonstrate that the proposed hybrid approach significantly outperforms conventional CNN models by mitigating overfitting and enhancing predictive performance. By leveraging the strengths of both architectures, the system ensures reliable diagnosis, supporting clinical decision-making. The findings of this study highlight the potential of deep learning in medical applications and pave the way for more robust and accurate automated diagnostic tools in hematology.

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