

Early Detection of Blood Cancer Using Deep Learning and Real-Time Web Deployment

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Abstract - Early detection of blood cancer, particularly leukemia, is critical for improving patient survival rates. Traditional diagnostic techniques such as manual microscopic examination are time-consuming and highly dependent on expert interpretation. This paper presents a deep learning-based approach for automated detection of blood cancer using microscopic blood smear images. A Convolutional Neural Network (CNN) model based on transfer learning with MobileNetV2 was developed and trained on preprocessed datasets. Preprocessing techniques included resizing, normalization, stain normalization, and data augmentation. The model achieved an accuracy of 89.25% with strong precision and recall performance. Unlike conventional studies, this work extends beyond model development by integrating the trained model into a real-time web-based application. The deployed system allows users to upload images and receive instant predictions, enhancing accessibility and practical usability. This study demonstrates the potential of combining deep learning with deployable systems for early medical diagnosis.

Key Words: Blood Cancer, Leukemia, Deep Learning, CNN, Medical Imaging, AI, Web Deployment

1. INTRODUCTION

Blood cancer, especially leukemia, originates in the bone marrow and disrupts normal blood cell production. Early diagnosis plays a crucial role in improving survival outcomes. Conventional diagnostic methods such as bone marrow biopsy and microscopic analysis are not only invasive but also time-intensive and subject to human error.

Recent advancements in artificial intelligence, particularly deep learning, have shown significant promise in medical image analysis. Convolutional Neural Networks (CNNs) are capable of identifying subtle morphological differences between healthy and cancerous cells. However, many existing studies focus primarily on model accuracy without addressing real-world deployment.

This study aims to bridge that gap by developing a robust CNN-based model and integrating it into a real-time web application, enabling accessible and efficient cancer detection.

2. Literature Review

Recent research highlights the effectiveness of deep learning in leukemia detection. CNN-based models have achieved

accuracy exceeding 97% on benchmark datasets. Studies emphasize the importance of recall in medical diagnosis to minimize false negatives.

Alternative approaches such as liquid biopsy and gene expression analysis have also been explored, offering non-invasive detection methods. However, these methods often require expensive equipment and complex processing.

Despite advancements, a major limitation remains the lack of deployable systems. This research addresses that limitation by combining high-performance modeling with real-time accessibility.

3. METHODOLOGY

3.1 Dataset

The dataset used in this study was obtained from publicly available sources, including leukemia image datasets from Kaggle (e.g., ALL-IDB and related blood smear datasets). The dataset was organized into training, validation, and testing subsets, with the final evaluation performed on a held-out test set (dataset_split/test).

The dataset consists of microscopic blood smear images categorized into two classes:

- Cancerous
- Non-cancerous

Data cleaning was performed to remove duplicate and low-quality samples, ensuring dataset reliability.

3.2 Data Preprocessing

To standardize input and improve model performance, the following preprocessing steps were applied:

- Resizing images to 224×224 pixels
- Normalizing pixel values to the range $[0,1]$
- Applying stain normalization to reduce colour variations
- Data augmentation techniques:
 - Rotation
 - Horizontal flipping
 - Zooming
 - Brightness adjustments

These steps improved generalization and robustness.

3.3 Model Architecture

A transfer learning approach using MobileNetV2 was employed.

The architecture includes:

- Pretrained MobileNetV2 base model
- Global Average Pooling layer
- Dense layer (128 neurons, ReLU activation)
- Dropout layer (0.5)
- Output layer (Sigmoid activation for binary classification)

This lightweight model is suitable for real-time deployment.

3.4 Training Configuration

- Optimizer: Adam
- Learning Rate: 0.0001
- Loss Function: Binary Cross entropy
- Metrics: Accuracy, Precision, Recall, F1-score

Training optimization techniques:

- Early Stopping
- ReduceLROnPlateau
- Model Checkpoint

4. RESULTS AND EVALUATION

4.1 Performance Metrics

The model achieved the following performance:

Metric	Value
Accuracy	89.25%
Precision	0.92
Recall	0.89
F1 Score	0.90

These results indicate strong classification performance, with high precision and balanced recall.

4.2 Class-wise Performance

Blood Cancer (Positive Class)

- Precision: 1.00
- Recall: 0.86
- F1 Score: 0.92

Normal (Negative Class)

- Precision: 0.70
- Recall: 1.00
- F1 Score: 0.82

4.3 Confusion Matrix Analysis

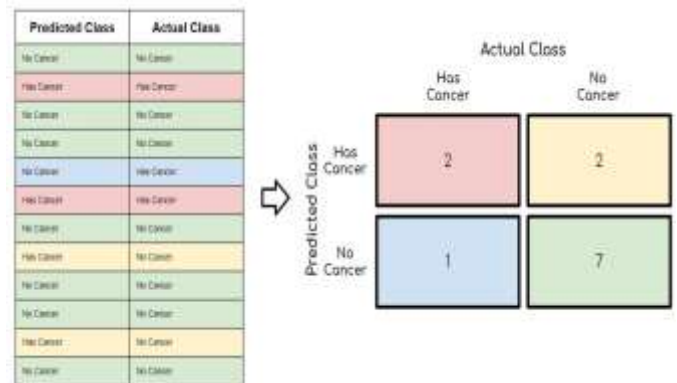


Figure 1: Confusion Matrix (based on test dataset predictions)

The confusion matrix reveals that the model achieves very high precision for cancer detection, meaning all predicted cancer cases are correct. However, the recall of 0.86 indicates that approximately 14% of actual cancer cases are misclassified as normal (false negatives).

This is a critical observation, as false negatives in medical diagnosis can delay treatment.

4.4 Performance Interpretation

The model demonstrates:

- **High precision (1.00) for cancer detection**, ensuring no false alarms
- **Moderate recall (0.86)**, indicating some missed cancer cases
- **Perfect recall (1.00) for normal class**, ensuring healthy samples are correctly identified

The lower precision (0.70) for the normal class is due to false negatives from the cancer class.

4.5 Key Observations

- The model is **highly reliable when predicting cancer**
- Some cancer cases are missed, which is a limitation
- Overall performance is balanced but can be improved

5. SYSTEM ARCHITECTURE



Figure 2: System Architecture

The system follows a client-server architecture:

1. User uploads a blood smear image
2. Backend preprocesses the image
3. Model performs prediction
4. Result is returned in real time

6. SYSTEM DEPLOYMENT

The trained model was deployed as a web application using Python, TensorFlow, and Gradio.

Users can:

- Upload images
- Receive predictions instantly

Resources:

- GitHub: <https://github.com/Sidhu242/blood-cancer-detection.git>
- Live App: <https://blood-cancer-detection-1.onrender.com/>

7. LIMITATIONS

- The model misses ~14% of cancer cases (false negatives)
- Dataset limitations may affect generalization
- Not clinically validated
- Dependent on image quality

8. CONCLUSION

This study presents a deep learning-based system for early detection of blood cancer using microscopic images. The model achieved an accuracy of 89.25% with strong precision and balanced recall.

The integration of the model into a real-time web application enhances accessibility and practical usability. While the system performs reliably, reducing false negatives remains an important area for improvement.

This system is intended as a decision-support tool and does not replace professional medical diagnosis.

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