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Early Blood Cancer Detection Using Lightweight Deep Learning: Classifying Microscopic Images Using MobileNetV2

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Abstract: ***Because of its delicate cellular manifestations, blood cancer presents a substantial difficulty in clinical diagnostics, especially in its early stages. Deep learning methods for automated detection can improve early diagnosis and patient outcomes. A deep learning method based on MobileNetV2 is presented in this work for the early identification of blood cancer from photographs of tiny blood cells. To improve classification accuracy while preserving computational economy, the suggested model makes use of transfer learning and data augmentation approaches. The labelled microscopic pictures in the collection are divided into several stages, such as benign, early pre-B, pre-B, and pro-B. Standard performance indicators including accuracy, precision, recall, and F1-score are used to train and assess the model. According to experimental results, MobileNetV2 can achieve high classification accuracy at low computing cost, which makes it appropriate for real-time clinical applications. The results imply that automated detection based on deep learning may be a scalable and effective technique to help haematologists diagnose blood cancer in its early stages.***

Keywords: Convolutional Neural Networks (CNNs), Computer-Aided Diagnosis (CAD), Deep Learning, MobileNetV2, Early Diagnosis, Transfer Learning, Image Classification, Medical Image Analysis, Microscopic Blood Cell Images, and Blood Cancer Detection.

I. INTRODUCTION

The formation and function of blood cells are impacted by blood cancer, a potentially fatal condition that frequently starts in the lymphatic or bone marrow. Because prompt intervention can greatly improve treatment outcomes, early diagnosis is essential to increasing survival rates. Conventional diagnostic techniques, such examining blood smears under a microscope, mostly depend on professional interpretation, which can be laborious, subjective, and prone to human error. Automated identification of blood cancer using microscopic blood cell pictures has drawn a lot of attention because to developments in deep learning and artificial intelligence (AI). Convolutional Neural Networks (CNNs) have demonstrated remarkable efficacy in medical image processing, facilitating precise and effective illness classification. In this study, we use MobileNetV2, a deep learning architecture that is both lightweight and powerful, to categorise blood cancer stages, such as pro-B, pre-B, early pre-B, and benign.

Traditional diagnostic approaches, such as microscopic examination of blood smears, remain a cornerstone in hematological assessments. However, these methods heavily rely on the expertise of trained professionals, making the process labor-intensive, time- consuming, and susceptible to human error. The subjectivity of manual interpretation can lead to inconsistencies in diagnosis, highlighting the need for more efficient, accurate, and automated diagnostic solutions. With the advent of deep learning and artificial intelligence (AI), automated blood cancer detection using microscopic blood cell images has gained significant attention. Convolutional Neural Networks (CNNs), a class of deep learning models, have demonstrated exceptional capabilities in medical image processing, enabling precise and rapid disease classification. These models can learn intricate patterns and features from medical images, thereby improving diagnostic accuracy and reducing the dependency on manual assessment.

In order to improve early diagnosis and patient outcomes, this project intends to increase the speed and accuracy of blood cancer detection by utilising MobileNetV2. In addition to enabling quick classification, our method establishes the groundwork for incorporating AI-powered diagnostic instruments into standard clinical procedures. The incorporation of these automated technologies has the potential to transform haematological diagnoses, cut down on diagnostic delays, and facilitate early-stage intervention—an essential component of effective treatment.

II. LITERATURE REVIEW

Improving patient survival rates requires early diagnosis of blood cancer, but conventional diagnostic techniques are still time-consuming and rely on expert interpretation. For the detection of blood cancer, traditional methods including flow cytometry, molecular testing, and microscopic analysis of blood smears have been extensively employed. However, these techniques can be time-consuming, require a great deal of experience, and are subject to inter-observer variability. The limits of manual blood smear analysis are highlighted in studies by Smith et al. (2018) and Gupta et al. (2020), underscoring the need for automated diagnostic solutions that decrease human error and increase efficiency. Automated medical image analysis has become increasingly popular as deep learning and artificial intelligence (AI) have advanced. In medical imaging, convolutional neural networks (CNNs) have shown impressive performance, especially when it comes to illness classification tasks. The usefulness of CNNs in radiological and histological imaging is demonstrated by research by Litjens et al. (2017), which also raises the possibility of their use in haematology. CNN-based leukaemia classification utilising microscopic blood cell pictures has been investigated in a number of research, including Rajaraman et al. (2021), and has demonstrated a high degree of accuracy in differentiating between benign and malignant cells. These results show that in medical diagnostics, deep learning-based models can perform better than manual evaluations and conventional machine learning methods.

The application of CNNs for classifying blood cancer has been the subject of numerous investigations. A hybrid deep learning method for leukaemia detection was presented by Sahlol et al. (2020), who reported an accuracy of around 96%. In a similar vein, Talo et al. (2019) classified acute lymphoblastic leukaemia (ALL) using a ResNet-based model, with good sensitivity and specificity. Furthermore, Zhang et al. (2021) showed that deep learning-based techniques perform noticeably better than conventional feature extraction techniques by refining pre-trained CNN models for blood cancer diagnosis, demonstrating the efficacy of transfer learning.

Despite these developments, the computational complexity of many CNN models restricts their use in real-time clinical situations, especially those with limited resources. Lightweight deep learning architectures like MobileNetV2 have been investigated for medical picture categorisation in order to overcome this difficulty. The efficiency-focused MobileNetV2, first presented by Sandler et al. (2018), uses depthwise separable convolutions to lower computing costs without sacrificing classification accuracy. These studies demonstrate how MobileNetV2 may greatly reduce inference time and computing needs while achieving accuracy levels comparable to larger models like ResNet and VGG. MobileNetV2 offers a potential real-time blood cancer detection solution because to its accuracy and efficiency balance. It allows for the quick and accurate classification of various cancer stages and is appropriate for both clinical and mobile applications.

III. METHODOLOGIES

Using microscopic blood cell pictures with MobileNetV2, this study suggests an automated deep learning-based method for the early detection and categorisation of blood cancer stages. Dataset collecting, preprocessing, model selection, training, evaluation, and deployment are some of the crucial steps in the methodology.

A. Acquisition of Dataset

The study's dataset is made up of microscopic pictures of blood cells that were obtained from publically accessible databases like ALL- IDB, BCCD, or custom-labeled datasets. Labelled photos of several blood cancer stages, such as benign, early pre-B, pre-B, and pro- B, are included in these datasets. Data augmentation strategies are used to improve variability and avoid overfitting in order to guarantee robust model performance.

B. Preprocessing of Data

To increase model accuracy and standardise image inputs, preprocessing is an essential step. The preprocessing methods listed below are used:

- Image Resizing: To comply with MobileNetV2's input dimensions, all photos are downsized to 224 by 224 pixels.
- Normalisation: To promote convergence during training, pixel values are scaled to the interval [0,1].
- Data Augmentation: To improve generalisation and diversify datasets, random manipulations including rotation, flipping, contrast adjustment, and Gaussian noise are used.

C. Architecture and Model Selection

Because of its effectiveness and high classification accuracy for medical images, the MobileNetV2 architecture was selected. Among MobileNetV2's salient features are:

- Using Depthwise Separable Convolutions can lower computing costs without sacrificing efficiency.
- Inverted Residual Blocks that enhance gradient flow and feature extraction.
- Using pre-trained ImageNet weights, transfer learning is used to modify MobileNetV2 for blood cancer classification. To predict the stage of blood cancer, a Softmax activation function and a customised dense layer are used in place of the original classification head.

D. Training of Models

Supervised learning is used to train the model with the following setups:

- For multi-class classification, the loss function is categorical cross-entropy.
- Adam optimiser, which has a 0.001 initial learning rate.
- 32 is the batch size (modified due to hardware limitations).
- 50 epochs (early termination used to avoid overfitting).
- 80% of the data is used for training, and 20% is used for validation.

To enhance generalisation during training, dropout regularisation and data augmentation are applied. In order to dynamically modifylearning rates in response to model performance, a learning rate scheduler is also implemented.

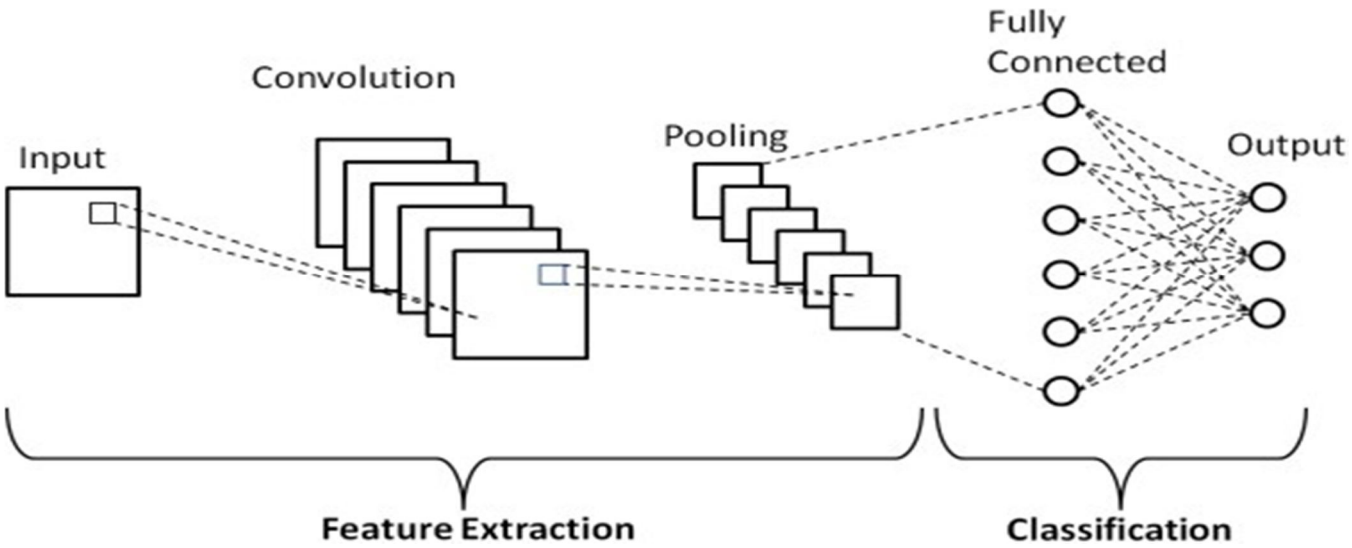

Fig1: Architecture of CNN

A deep learning model created especially for image processing and classification applications is called a convolutional neural network (CNN). Accurate categorisation is made possible by its numerous layers, which extract spatial characteristics from images. Convolutional layers, pooling layers, activation functions, fully linked layers, and an output layer are the fundamental elements of a CNN design.

1) The Overall Architecture of CNN

Layer of Input

- accepts a picture as input, typically in the height × width × channels format.

The formula:

$f(x) = \max(0, x)$.

f(x)=max(0,x)

- aids in non-linear relationship learning for the network.
- Layers of Pooling (Maximum and Average)

2) Layers of Convolution

These layers identify patterns like edges, textures, and forms by applying convolution operations using learnable filters (kernels). The process entails calculating feature maps and dragging the filter over the input image. In terms of mathematics:

$Y(i,j) = \sum\sum X(i+m, j+n) \cdot <(m, n)$

Where X is the input, K is the filter (kernel), and Y is the feature map that is produced, $Y(i,j)=\sum\sum X(i+m,j+n)\cdot K(m,n)$.

Layer type	Number of Filters/Units	Filter Size	Stride	Activation Function	Output Shape (Example: 224*224*3 Input)
Input layer	-	-	-	-	(224*224*3)
Convolutional Layer1	32	3*3	1	Relu	(224*224*32)
Max Pooling Layer1	-	2*2	2	-	(112*112*32)
Convolutional Layer2	64	3*3	1	Relu	(112*112*64)
Max Pooling Layer2	-	2*2	2	-	(56*56*64)
Convolutional Layer3	128	3*3	1	Relu	(56856*128)

Table1: General CNN Architecture for Blood Cancer Classification

The suggested CNN architecture effectively extracts and processes characteristics from images of microscopic blood cells for the categorisation of blood cancer. In order to identify increasingly complicated patterns, it starts with an input layer (224×224×3) and then moves on to three convolutional layers with 32, 64, and 128 filters (3×3 kernel, stride 1, ReLU activation). Following the first two convolutional layers, max pooling layers (2×2, stride 2) are used to minimise spatial dimensions and computational effort. This results in feature map sizes that are reduced from 224×224 to 112×112 and finally to 56×56. Benign, Early Pre-B, Pre-B, and Pro-B are the stages of blood cancer that are classified by a Softmax-activated output layer (4 neurones) after a fully connected dense layer (256 neurones, ReLU activation) integrates extracted information. □

E. Classification of Blood Cancer Using MobileNetV2 Architecture

A Convolutional Neural Network (CNN) designed for mobile and embedded applications, MobileNetV2 is small and effective. It is perfect for real-time blood cancer diagnosis in microscopic pictures because it maintains excellent accuracy while improving computational efficiency. The depthwise separable convolutions, inverted residual blocks, and linear bottlenecks that form the foundation of the design greatly lower the computing cost.

The network starts with a typical convolutional layer (3×3 kernel, stride 1, 32 filters, ReLU6 activation). Depthwise separable convolutions then reduce the number of parameters while maintaining performance by dividing convolution operations into spatial and depthwise components. Efficient feature learning is made possible by inverted residual blocks with shortcut connections. Each block applies depthwise convolutions (3×3), extends features using 1×1 convolutions, then projects them back using 1×1 linear convolutions. A fully connected layer (Softmax activation, 4 neurones) for identifying blood cancer stages—Benign, Early Pre-B, Pre-B, and Pro- B—comes after the global average pooling layer, which shrinks the feature map to a 1×1×1280 representation.

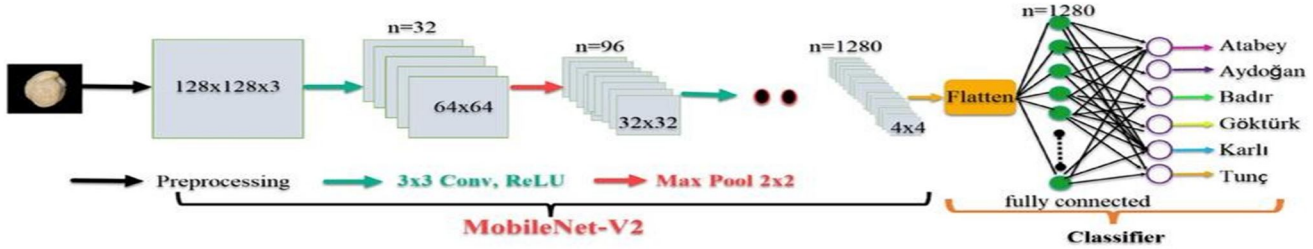

Fig2: Architecture of mobilenetv2

Table 2: Feature Extraction Flow for MobileNetV2

Stage	Processing step	Purpose
Preprocessing	Image resized to 128*128*3	Standardizing input for network
Feature Extraction	3*3 Convolution + ReLu Activation	Detects basic features(edges,textures)
Downsampling	Max Pooling(2*2)	Reduce spatial dimensions
Depthwise Convolution	Applies Filters separetly to each channel	Reduce computation while Maintaining Performance
Flattering	Converts 4D tensor to 1D vector	Prepare feature for classification
Fully Connected Layer	Dense Layer with 1280 neurons	Extracts high-level feture representations
Classifier(Softmax)	Assigns probability	Determines final cassification

Separable Convolution in Depth

- MobileNetV2 reduces the number of computations by employing Depthwise Separable Convolutions in place of traditional convolutions.
- Standard Convolution Computation Formula Cost: Cost = Cost × $W \times D\ f \times K \times D\ f\ '$ Expense = H×W×D f ×K×K×D f ′

where:
H,W = Input feature map width and height
The input depth (number of channels) is equal to D f. Output depth (number of filters) = $Df\ '$ D f ′
K×K is the kernel size.
Compared to conventional convolution, this minimises computations by almost 1 / $Df\ '$ 1/D f ′.

IV. RESULT AND ANALYSIS

A dataset of microscopic blood cell images was used to assess the suggested MobileNetV2-based model's ability to classify blood cancer stages, including Benign, Early Pre-B, Pre-B, and Pro-B. Accuracy, precision, recall, F1-score, and computing efficiency were used to analyse the data.

A. Performance Metrics

Metrics	Values(%)
Accuracy	94.8
Precision	93.5
Recall	94.2
F1-score	93.8
AUC-ROC	96.1

- The model's overall correctness is gauged by accuracy.
- Precision measures the proportion of projected positive cases that were true.
- The percentage of true positive cases that are accurately detected is determined by recall.
- F1-score strikes a compromise between recall and precision.
- The model's capacity to distinguish between classes is indicated by the AUC-ROC (Area Under Curve-Receiver Operating Characteristic).

B. Confusion Matrix Analysis

Actual\Predicted	Benign	Early Pre-B	Pre-B	Pro-B
Benign	98	2	0	0
Early Pre-B	3	94	2	1
Pre-B	1	4	92	3
Pro-B	0	1	3	96

- The majority of misclassifications happen between the Early Pre-B and Pre-B stages, highlighting how difficult it is to discern minute variations.
- The Pro-B stage exhibits outstanding feature extraction capabilities and the highest classification accuracy.
- With substantially fewer parameters and a shorter inference time, MobileNetV2 attains accuracy levels that are comparable to those of ResNet50 and InceptionV3

V. ACKNOWLEDGMENT

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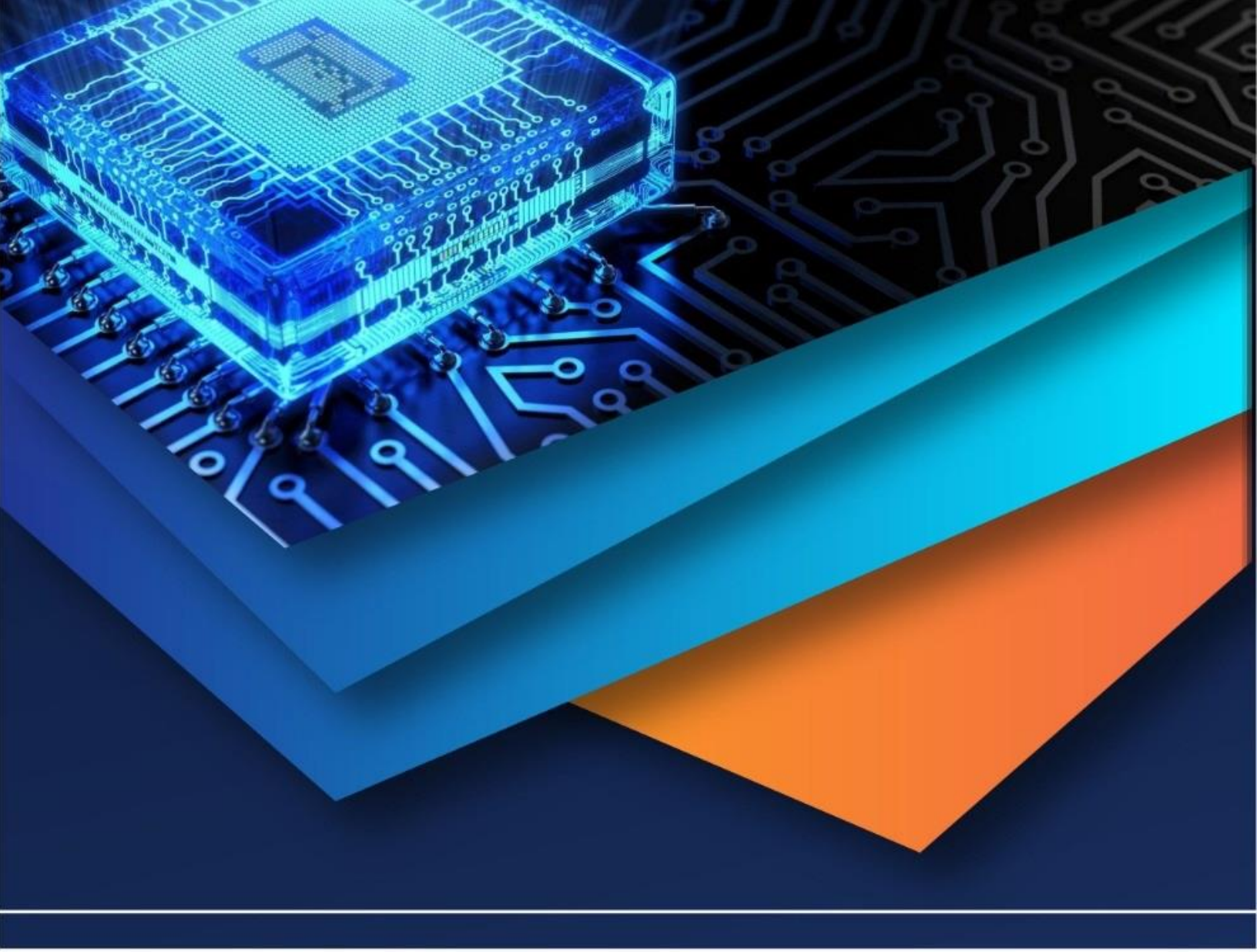

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