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Automated blood cancer detection models based on EfficientNet-B3 architecture and transfer learning

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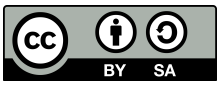
ABSTRACT

In blood smear images, there are difficulties in diagnosing blood cancer diseases like leukemia and lymphoma because of their various forms that appear in the human body. In this paper, a method for automatic detection of blood cancer is suggested that uses the EfficientNet-B3 architecture along with transfer learning techniques to improve accuracy and efficiency. We first fine-tuned the EfficientNet-B3 model, which was pre-trained on a large dataset consisting of annotated blood smear images, to capture pertinent features linked with blood malignant cells. To expedite the training process and adapt the model to our task, we use transfer learning. The proposed approach's results from our experiments show that it outperforms traditional deep learning models and state-of-the-art methods in blood cancer detection. Additionally, with high precision and recall rates, this model also detects different types of blood cancers with robustness in its performance since its accuracy is over 99%. This means that when used together with the EfficientNet-B3 architecture, transfer learning can help the developed methods generalize among different types of blood cancers and conditions.



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1. INTRODUCTION

Understanding blood cancer is essential for developing accurate diagnostic and treatment approaches [1]–[3]. Hematologic malignancy, commonly referred to as blood cancer, arises in the bone marrow or lymphatic system, impacting the generation and operation of blood cells. These diseases, including leukemia, lymphoma, and myeloma, are part of a varied group. Each disease has its unique characteristics and requires specific treatment methods. Blood cancer develops through genetic abnormalities that cause unregulated cell growth and a weakened immune response. This leads to a complicated interaction between the cancerous cells and the surrounding microenvironment [4].

Exploring blood cancer is critical to tailoring effective diagnostic and therapeutic strategies. Blood cancer, also known as hematologic malignancy, is a disease of the bone marrow and lymphatic system that ultimately affects blood cells' production and functional capabilities. The blood cancer-like coexisting diseases encompass leukemia, lymphoma, and myeloma, which possess unique characteristics and therapeutic regimens. Genetic mutations that induce unrestricted cellular multiplication and impaired immune response are responsible for leading to blood cancer. The tumor interactome is a complex network that evolves during the growth of tumors. So, understanding the tumor network makes it easier to find the very important signs of cancer and figure out how they work at the molecular level [4]. Blood cancer is important for the development of effective diagnostic and therapeutic approaches to treatment. Blood cancer, or hematologic malignancy, arises in the bone marrow or the lymphatic system and disrupts the production and function of blood cells. This group of diseases is very diverse and includes leukemia, lymphoma, and myeloma, among others, which also differ in characteristics and approaches to treatment. Mutations that cause unchecked cell division and reduce immune activity are what lead to blood cancer. In the context of these processes, complex conditions arise for the interaction of the tumor cells [4].

Deep medical imaging learning has utterly changed the game by providing diagnostics, treatment planning, and patient care that is highly accurate and effective. With amazing accuracy, various deep learning architectures such as convolutional neural networks (CNNs) have been able to help researchers find and diagnose different medical conditions [5]–[9]. For example, EfficientNet-B3 architecture has shown good performance in classifying subtypes of blood cancer using medical imaging data. To learn complex patterns and features from large datasets that facilitate accurate predictions with high sensitivity and specificity, deep learning algorithms are trained. This technological breakthrough can greatly enhance early detection rates as well as treatment outcomes for blood cancers, thereby saving more lives while improving the quality of life among patients in general. Further research in this direction holds great promise for the future of medical imaging in the field of oncology [10]. Deep learning approaches, like the EfficientNet-B3 architecture, show promise for analyzing huge amounts of data from genetic profiling, diagnostic tests, and treatment outcomes. This will help us learn more about how blood cancer is different in each person and provide more personalized care. By unraveling the intricacies of blood cancer at a molecular level, researchers can pave the way for targeted therapies and improved patient outcomes [11]. However, it is important to note that the development of such systems should be done in collaboration with medical experts, who can provide valuable insights and guidance throughout the process [12]. By utilizing deep learning CNN algorithms, blood cancer classification can be greatly improved in terms of accuracy and efficiency. The EfficientNet-B3 architecture in blood cancer detection represents a groundbreaking approach that harnesses the power of deep learning to enhance diagnostic accuracy and efficiency. Researchers can look at complicated images of blood cancer with a level of accuracy that has never been seen before, thanks to EfficientNet-B3's superior feature extraction capabilities. This allows for early detection and personalized treatment plans. Additionally, EfficientNet-B3's ability to grow and change makes it perfect for handling large amounts of medical imaging data, which makes it easier to quickly and accurately diagnose different types of blood cancer.

By integrating this cutting-edge deep learning model into medical practices, healthcare professionals can use sophisticated technology to change the way they detect and treat blood cancer, thereby improving patient outcomes and advancing oncology. They have been effective in many medical imaging tasks that relate to blood cancers but are not limited to early diagnosis and personalized treatment by EfficientNet-B3 architectures, for instance. This study therefore intends to demonstrate how this particular architecture can be used in analyzing different kinds of blood cancer images to improve their identification and classification accuracy. The main goal of this research is to investigate the EfficientNet-B3 architecture on medical images for better detection abilities for various forms of leukemia or lymphoma. In other words, what would happen if we let deep learning loose on all those patient records? Such an examination would not only push forward our understanding of cancer but also help us save lives more effectively. There are five parts in the manuscript, including a literature review (section 2), proposed work (section 3), results with relevant comments (section 4), and conclusion (section 5).

2. RELATED WORK

The many characteristics of blood cancers, such as myeloma, leukemia, and lymphoma, make diagnosis and categorization very difficult. Conventional approaches rely significantly on laborious and subjective

histopathological analysis, genetic profiling, and clinical data processing. Deep learning has recently come into its own as an effective tool for blood cancer categorization, with the ability to enhance precision, efficacy, and individualized treatment approaches. While investigating several deep learning applications, this section highlights key approaches, breakthroughs, and challenges in blood cancer categorization. The researchers [11], [13], [14] used CNNs to analyze microscopic images of blood samples, one of the most widely recognized deep learning applications in blood cancer categorization. CNNs' exceptional ability to capture complex characteristics and patterns within these images enables accurate subtype classification of blood cancers based on cellular morphology. To better categorize blood cancers, researchers have developed CNN architectures tailored to the task. To train algorithms that can distinguish between normal and diseased cells based on minor variations, they used massive annotated datasets. These models provide a faster and more objective alternative to standard manual evaluation methods, and they have demonstrated promising results in automated diagnosis and subtype identification [15]–[17]. The availability of annotated data presents a problem in blood cancer categorization, particularly for rare subtypes or less prevalent presentations. One useful strategy for dealing with the data limits of deep learning is transfer learning, which involves taking what you've learned and applying it to a new related task. We can fine-tune pre-trained models to respond to specific classification tasks using smaller annotated blood cancer datasets. These models are typically trained on large-scale image datasets, like Image-Net. When you combine features from different datasets with sparsely annotated data, this is called transfer learning. It helps deep learning models classify blood cancer better across different datasets [18], [19].

In addition to using individual deep learning models, certain research papers have developed hybrid deep learning frameworks for leukemia cancer diagnosis. Yosinski *et al.* [18] introduced a hybrid approach that utilizes ResNet50, VGG16, and VGG19 which are advanced CNNs, to automate cell identification. They compare their proposed method with K-nearest neighbors (KNN), logistic regression (LR), support vector machine (SVM), and decision tree (DT). The proposed technique achieves 88.50% accuracy in cell identification. Yosinski *et al.* [18] created a hybrid model using two CNN architectures to enhance accuracy in deep learning. Testing the suggested procedure on 636 blood samples with healthy and acute lymphoblastic leukemia (ALL) cells yields an accuracy of 89.70%. Together, the vision transformer and CNN-based model extract many cell features in diverse ways, improving classification results. They improved an uneven dataset using enhancement-random sampling (DERS). The algorithm achieves 99.03% accuracy, proving its effectiveness as a computer aided design (CAD) system for ALL. Kasani *et al.* [20] developed a hybrid method that combines VGG16 and MobileNet to extract the profound characteristics, which are then used for the categorization of leukemic B-lymphoblast [20]. Their proposed methodology incorporates multiple data augmentation techniques and achieved an accuracy of 96.17%, a sensitivity of 95.17%, and a specificity of 98.58%. In addition, the researcher in [21] combined the NASNetLarge and VGG19 deep machine learning models to classify leukemic B-lymphoblast cells and normal B-lymphoid precursor cells, achieving a detection accuracy of 96.58%. Their suggested model accurately detects acute lymphoblastic leukemia, and they demonstrate that ensemble learning is significantly superior to a single model. To address the problem of classifying blood cancer, our suggested deep learning model makes use of the EfficientNet-B3 model and transfer learning. By using this method, the traditional deep learning model's accuracy is improved, and the images are classified as either positive or negative blood samples.

3. METHOD

EfficientNet-B3 architecture, an advanced neural network model [22], has shown promising results in various deep learning applications, including medical image analysis for detecting blood cancer. This architecture, characterized by its increased depth and breadth in comparison to previous models, achieves a harmonious equilibrium between the complexity of the model and its computational efficiency. The EfficientNet-B3 model uses efficient building blocks, like mobile inverted bottleneck convolution and squeeze-and-excitation blocks, to improve performance while keeping the cost of computing low. Furthermore, it employs compound scaling to effectively increase the network's depth, width, and resolution at the same time, hence improving its ability to represent information without a substantial increase in resources. The EfficientNet-B3 design exhibits robustness and effectiveness, rendering it a favorable option for the precise classification of blood cancer jobs. Furthermore, it exhibits superior performance when used with extensive collections of images [22]. The investigation and application of this structure emphasize its capacity for enhancing deep learning techniques for the interpretation of medical images, specifically in the field of oncology research.

3.1. The dataset

We obtained the dataset for this work from supplementary data sources, specifically Kaggle [23]. The collection comprises 3,262 authentic photographs of blood vessel stains. Out of the 89 subjects whose photographs were included, 64 were thought to have ALL, while the remaining 25 were assessed to be normal. We initially divided the dataset into two identical categories: benign and malignant, before organizing it into four primary groups with three subtypes of cancer (benign, early pre-B, pre-B, and pro-B). The photographs were captured with a Zeiss camera mounted on a microscope at a magnification level of 100× and saved in JPG format. An expert conducted a comprehensive and conclusive investigation using flow cytometry to determine the types and subtypes of these images.

3.2. Transfer learning

Transfer learning, or domain adaptation, is a conceptual framework that leverages knowledge from one area to address related tasks [5], [6], [24]. In this regard, the study authors utilized their parameters on the ImageNet dataset, which holds great significance in deep learning applications. Transfer learning is a type of semi-supervised learning method that reduces the need for labeled data, especially in situations where there is a limited amount of data available for collection [25]. An outstanding advantage of this strategy is its remarkable capacity to effectively generalize across various jobs. The study effectively employed transfer learning and fine-tuning strategies to develop EfficientNet-B3, showcasing its efficacy in tackling similar jobs.

3.3. Proposed EfficientNet-B3 model

Once the transfer learning model is utilized. The primary focus of this study was on the EfficientNet family of models, with particular emphasis on EfficientNet-B3, as shown in Figure 1. The goal of EfficientNet models is to find a good balance between accuracy and efficiency in CNNs by using a unique method called compound scaling. This method equally adjusts the width, depth, and quality characteristics by applying pre-determined factors. EfficientNet-B3, as a member of this group, exemplifies this equilibrium by employing a customized architecture that provides significant generalizability.

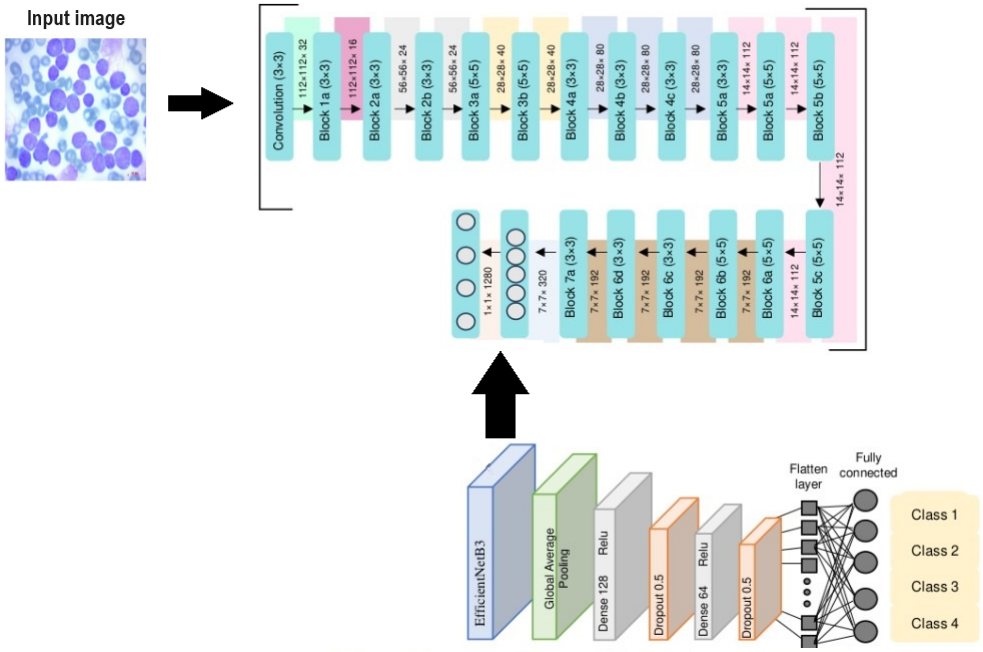


Figure 1. Architecture of the proposed work [22]

For our model creation, we utilized the Keras library to create an instance of EfficientNet-B3 as the foundational model, which was already trained on ImageNet and had pre-existing weights. To optimize the use of the already trained features, we immobilized the initial half of the layers. Afterward, we incorporated more customized layers into the existing model. A global average pooling layer was used to make the space smaller,

and then two dense layers (128 and 64 pixels) used rectified linear unit (ReLU) activation functions. Dropout layers with a dropout rate of 0.5 were selectively included to implement regularization and mitigate the risk of overfitting [26], [27]. The last layer, a dense layer with softmax activation, was set up for our multi-class classification problem with 4 classes. This model, characterized by its unique design, has proven to be highly effective in accurately capturing complex patterns, particularly in photographs of superior quality. Using the compound scaling method, EfficientNet-B3 was able to find a good balance between the model's parameters, accuracy, and how quickly it could do its work.

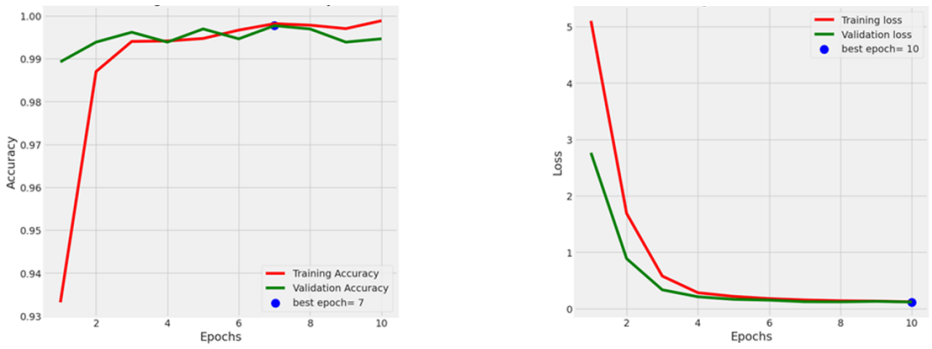
4. RESULTS AND DISCUSSION

This section analyses the results from experiments using deep learning models. This section gives an evaluation analysis using a state-of-the-art model. The suggested model was evaluated using various performance matrices, including accuracy (A), precision (P), recall (R), and F1-score with state-of-the-art model [28]–[30]. Table 1 depicts that this highly advanced neural network architecture, the EfficientNet-B3 architecture, yields good performance in medical image analysis targeted to identify blood cancer and can be used for a wide range of deep learning applications. It is deeper and wider compared to the model on which it is built, while still balancing between the complexity of the model and the computational efficiency. The EfficientNet-B3 model uses efficient building blocks-e.g., mobile inverted bottleneck convolution blocks and squeeze-and-excitation blocks-to enhance performance while keeping the cost of computing very low. Compound scaling is also adopted to scale the depth, width, and resolution of a network all at the same time in a resource-efficient manner.

Table 1. The overall performance of different Pre-trained CNN models

CNN model	Precision	recall	F1-score
VGG19	96.64	96.87	96.75
ResNet50	98.28	98.32	98.30
Inception V3	77.82	75.68	75.76
Inception + Xception	87.71	84.27	85.06
Proposed research	99.00	99.00	99.00

Figure 2 illustrates the projected network's accuracy of 99%. Figure 2(a) displays an accuracy curve that shows the relationship between the number of epochs (horizontal axis) and the range of accuracy (vertical axis). Augmenting the number of epochs results in enhanced detection accuracy. According to Figure 2(b), increasing the number of epochs decreases the loss of the detection network.



(a) (b)

Figure 2. The plots diagram of proposed architecture (a) training and validation accuracy and (b) training and validation loss

The EfficientNet-B3 architecture's robustness and efficiency make it a promising candidate for accurate blood cancer classification tasks, offering improved performance on complex image datasets. The ex-

ploration and utilization of this architecture highlight its potential for advancing deep learning methodologies for medical image analysis, particularly in oncology research. In addition, transfer learning has had transformative effects on blood detection deep learning models by improving accuracy, reducing data requirements, enhancing generalization and domain adaptation, and promoting accessibility for medical professionals. It has facilitated advancements in research and clinical applications, paving the way for more effective and efficient blood detection in healthcare settings.

5. CONCLUSION

As a result, the conclusion shows that the EfficientNet-B3 architecture works well for deep learning models that use transfer learning to find and classify blood cancer. The high accuracy and efficiency of the model in discriminating between different types of blood cancer cells indicate that this method may improve diagnostic procedures in actual clinical settings. Besides, it can be argued that the model's ability to deal with different types of datasets could be extremely complex and divergent, which reveals its robustness and scalability. To further our knowledge, there must be additional work to explore the full potential and limitations of this architecture as a means for detecting blood cancer, as well as refining it for real-time applications. Deep learning integrates with innovative architectures, which allow us to push forward medical imaging and diagnosis to realize better patient outcomes. To conclude, deep learning combined with cutting-edge architectural designs will revolutionize medical imaging, thereby enhancing patient results and healthcare delivery.

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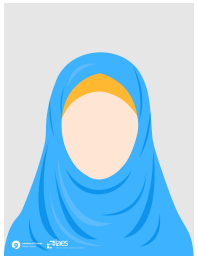

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