Journal of Electronics, Electromedical Engineering, and Medical Informatics
Multidisciplinary: Rapid Review: Open Access Journal Vol. 7, No. 2, April 2025, pp: 557-566; eISSN: 2656-8632

RESEARCH ARTICLE OPEN ACCESS

Manuscript received January 30, 2025; accepted March 20, 2025; date of publication April 23, 2025
Digital Object Identifier (**DOI**): https://doi.org/10.35882/jeeemi.v7i2.703

How to cite: D. Shamia, R. Umapriya, M.L.M. Prasad, Rini Chowdhury, Prashant Kumar, and K. Vishnupriya "Enhancing Skin Cancer Classification with Mixup Data Augmentation and Efficientnet", Journal of Electronics, Electromedical Engineering, and Medical Informatics, vol. 7, no. 2, pp. 557-566, April 2025.

Enhancing Skin Cancer Classification with Mixup Data Augmentation and Efficientnet

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ABSTRACT Skin lesion classification and segmentation are two crucial tasks in dermatological diagnosis, here automated approaches can significantly aid in early detection and improve treatment planning. The proposed work presents a comprehensive framework that integrates K-means clustering for segmentation, Mixup augmentation for data enhancement, and the EfficientNet B7 model for classification. Initially, K-means clustering is applied as a pre-processing step to accurately segment the lesion regions from the background, ensuring that the model focuses on processing the most relevant and informative features. This segmentation enhances the model's ability to differentiate between subtle lesion boundaries and surrounding skin textures. To address the common issue of class imbalance and to improve the overall robustness of the classification model, Mixup augmentation is employed. This technique generates synthetic samples by linearly interpolating between pairs of images and their corresponding labels, effectively enriching the training dataset and promoting better generalization. For the classification task, EfficientNet B7 is utilized due to its superior feature extraction capabilities, optimized scalability, and excellent performance across various image recognition challenges. The entire pipeline was evaluated on a dataset comprising 10,015 dermatoscopic images covering seven distinct categories of skin lesions. The proposed method achieved outstanding performance, demonstrating a precision rate of 95.3% and maintaining a low loss of 0.2 during evaluation. Compared to traditional machine learning and earlier deep learning approaches, the proposed framework showed significant improvements, particularly in handling complex patterns and imbalanced datasets, making it a promising solution for real-world clinical deployment in dermatology.

INDEX Skin Cancer Classification, EfficientNet, MixUp Data Augmentation, Dermoscopic Images, Deep Learning.

I. INTRODUCTION

Skin cancer is one of the most prevalent and increasingly concerning types of cancer worldwide, with melanoma being the deadliest and most aggressive form [1]. It is estimated that skin cancer is responsible for more than 2 million cases annually, a number that continues to rise, largely due to increased sun exposure, tanning bed use, and the depletion of the ozone layer [2]. Non-melanoma skin cancer (NMSC) accounts for the majority of cases, with over 9 million cases reported globally each year. Melanoma, although less common, is the most fatal of skin cancers, accounting for over 200,000 new cases annually, with a significant number of those cases diagnosed in advanced stages [3]. Skin cancers have high potential for metastasis, especially melanoma, which can spread rapidly to other organs if not detected early. Early detection and timely intervention are critical to improving survival rates for skin cancer patients, as they can dramatically increase the chances of effective treatment and remission. When melanoma is diagnosed at an early stage, the 5-year survival rate is as high as 98%, but this survival rate drops dramatically to only 23% when the cancer metastasizes to distant parts of the body, highlighting the urgent need for early diagnosis and prompt clinical action.

Dermatologists often encounter difficulties in distinguishing between benign and malignant lesions due to the vast heterogeneity in lesion morphology, color, size, and texture, as well as variations in the appearance of skin cancers across different skin types [4] . Additionally, subtle changes in skin lesions can be easily overlooked, especially in cases of early-stage melanoma, where lesions may appear similar to benign moles or skin conditions [5]. The reliance on clinical expertise alone increases the risk of misdiagnosis or delayed diagnosis, especially in settings with a shortage of experienced dermatologists or in rural and underserved areas where access to specialists is limited. Furthermore, human error and fatigue may contribute to diagnostic inconsistencies, making it challenging to maintain high standards of accuracy across a wide range of cases[6]. These challenges underscore the importance of developing automated systems that can assist in the accurate, efficient, and consistent classification and segmentation of skin lesions, thus supporting dermatologists in their decision-making processes and potentially reducing diagnostic errors [7]. By leveraging technological advancements, these automated systems can provide real-time, reliable diagnostic support, which is particularly crucial in urgent clinical environments and for early-stage skin cancer detection [7].

Skin cancer is frequent malignancies worldwide, with its occurrence increasing due to several factors, including increased exposure to UV radiation for extended periods, environmental effects, and hereditary predisposition [8]. Accurate detection of skin cancer is essential to better survival outcomes in patients as advanced stages are more difficult to treat [9]. Advances in diagnostic techniques notwithstanding, manual methods like dermoscopic analysis have a robust requirement for extensive expertise and are highly time-consuming, opening space for constructing efficient and automated diagnostic tools [10]. Skin cancer classification is a challenging task because there are numerous types of lesions, slight differences between the benign and malignant ones, and noise in the images of dermoscopic impressions is caused by various types of artifacts and lighting variations [1], [2] .

Another issue is inter-class similarity like benign keratosis and actinic keratosis. This complexity cannot be easily captured by traditional machine learning approaches. Therefore, there is a huge need for deep learning architectures that work strongly under such challenges with high accuracy [3]. The medical image task gives a clear instance where an excellent deep learning architecture, EfficientNet, has showcased quite reliable performance. It is capable of scaling depth, width, and resolution with efficiency to ensure high performance while keeping computational overhead low [4]. In the context of skin cancer classification, EfficientNet is quite effective in extracting critical features from high-resolution dermoscopic images like intra-class variability and inter-class similarity [11]. Its computational efficiency makes it an ideal choice for practical deployment in resource-constrained environments, such as primary care clinics and remote areas. Data augmentation also is a central part of improving performance for deep models, especially under low data volumes or class-imbalanced scenarios [5].

MixUp is a strong augmentation method that creates synthetic training images by combining pairs of images with their corresponding labels (FIGURE 1). In doing so, it serves not only as an augmentation of the dataset but also as regularization of the model, such that the risk of overfitting is significantly lowered while enhancing generalization [6]. The contributions of the paper are as follows,

1. This paper integrates MixUp into EfficientNet, thereby enabling the use of diverse and augmented datasets to further boost its ability to classify seven types of skin cancer accurately.
2. Develop an advanced skin cancer classification framework by combining EfficientNet with MixUp data augmentation. The focus is on classifying seven distinct categories of skin cancer using a robust, augmented training pipeline.
3. By leveraging the strengths of EfficientNet and MixUp, this work addresses key challenges in skin cancer diagnosis, such as inter-class similarity, dataset imbalance, and model robustness.

The rest of the article is as follows, Section II presents the related work; Section III draws the proposed architecture. Section IV discusses the results obtained using the proposed architecture and comparative analysis with existing state of art models. Section V concludes the proposed work and directions for future work.

II. STATE-OF-THE-ART TECHNIQUES

Deep learning, particularly Convolutional Neural Networks (CNNs), has become the cornerstone of skin cancer classification. Early work by [9] demonstrated the potential of deep learning in dermatology by training a CNN on a large dataset of skin lesion images, achieving performance comparable to dermatologists. This study laid the foundation for subsequent research, which has focused on optimizing CNN architectures to improve diagnostic accuracy [10]. For example, advanced architectures like EfficientNet and DenseNet have been widely adopted due to their ability to balance computational efficiency and accuracy. Emphasized the importance of transfer learning, where pre-trained models on ImageNet are fine-tuned for skin lesion datasets, achieving state-of-the-art results[11] . Ensemble learning has also gained traction, with an ensemble of multiple CNNs to combine their predictions, thereby improving robustness and accuracy. This approach has proven effective in handling the high variability in skin lesion appearances [12].

One of the major challenges in skin cancer classification is the imbalanced nature of datasets, where certain types of skin lesions are underrepresented [13]. To address this, researchers have employed techniques such as data augmentation and synthetic data generation [14]. Data augmentation methods, including rotation, flipping, scaling, and color jittering, have been widely used to increase dataset diversity and reduce overfitting. Synthetic data generation using Generative Adversarial Networks (GANs) has also shown promise. For instance, [15] used GANs to generate realistic synthetic skin lesion images, which helped balance underrepresented classes and improved model performance. Additionally, techniques like class weighting and focal loss have been employed to mitigate the impact of class imbalance during model training [16].

Explainable AI (XAI) has emerged as a critical area of research in skin cancer classification, as it provides insights into the decision-making process of deep learning models. This is particularly important in medical applications, where transparency and interpretability are essential for gaining the trust of clinicians [17][. Techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping) and LIME

(Local Interpretable Model-agnostic Explanations) have been widely adopted to visualize the regions of an image that contribute most to the model's predictions [18]. For example, here used Grad-CAM to highlight the areas of skin lesions that were most influential in the model's classification, providing valuable insights into its decision-making process. This not only improves interpretability but also helps identify potential biases or errors in the model [19].

The integration of multi-modal data has also been explored to enhance skin cancer classification. While most studies rely on dermoscopic images, combining these with clinical metadata, patient history, and other imaging modalities has shown promise. Here proposed a multi-modal approach that integrates dermoscopic images with patient metadata, such as age, gender, and lesion location, to improve classification accuracy [20]. Similarly,[21] explored the use of multi-task learning, where a single model is trained to perform multiple related tasks, such as lesion segmentation and classification, simultaneously. This approach leverages shared features between tasks to improve overall performance [22]. Despite these advancements, several challenges remain in the field of skin cancer classification. One major challenge is the lack of standardized datasets and evaluation metrics, which makes it difficult to compare the performance of different models. Additionally, the generalizability of models trained on specific datasets to real-world clinical settings remains a concern [23]. To address this, researchers have emphasized the importance of external validation and the use of diverse datasets that reflect the variability seen in clinical practice [24]. Another challenge is the ethical and regulatory considerations surrounding the use of AI in healthcare, particularly regarding patient privacy and data security.

[9]proposes a new deep learning architecture for skin cancer detection using a combination of ConvNeXtV2 as a convolutional neural network with focal self-attention mechanisms. The focus of the research is on enhancing the accuracy of detection through the use of attention mechanisms that can focus on specific regions of an image for classification in skin cancer . [10] proposed a model Deep Belief Network (DBN) coupled with optimal feature selection techniques. The proposed method improves the model's ability to accurately classify skin cancer by selecting the most relevant features [7]. [11] introduce an efficient Improved Adaboost Aphid–Ant Mutualism (IA-AAM) model. The model combines boosting techniques with a mutualistic optimization approach to enhance classification performance [10].

[12] presents a dynamic-context cooperative quantum-behaved particle swarm optimization technique for multi-level thresholding in medical image segmentation. This optimization technique is applied to the proposed method of segmenting medical images with applications in skin cancer detection, among other things. [13] discusses a novel deep learning framework based on the Swin Transformer for dermal cancer cell classification. It uses a transformer-based architecture to improve the classification of skin cancer cells, showing how deep learning can be applied to cell-level detection. [14]) proposed a hyper-parameter optimized approach for skin cancer image segmentation, using an enhanced Grey Wolf Optimizer (GWO) algorithm over the traditional Fully Convolutional Encoder-Decoder Network (FCEDN). This allows the model to fine-tune its hyper-parameters for optimized performance in segmentation of skin cancers [14]. [15] proposed an Efficient Fusion of Transformers' SelfAttention with CNN's Features. It

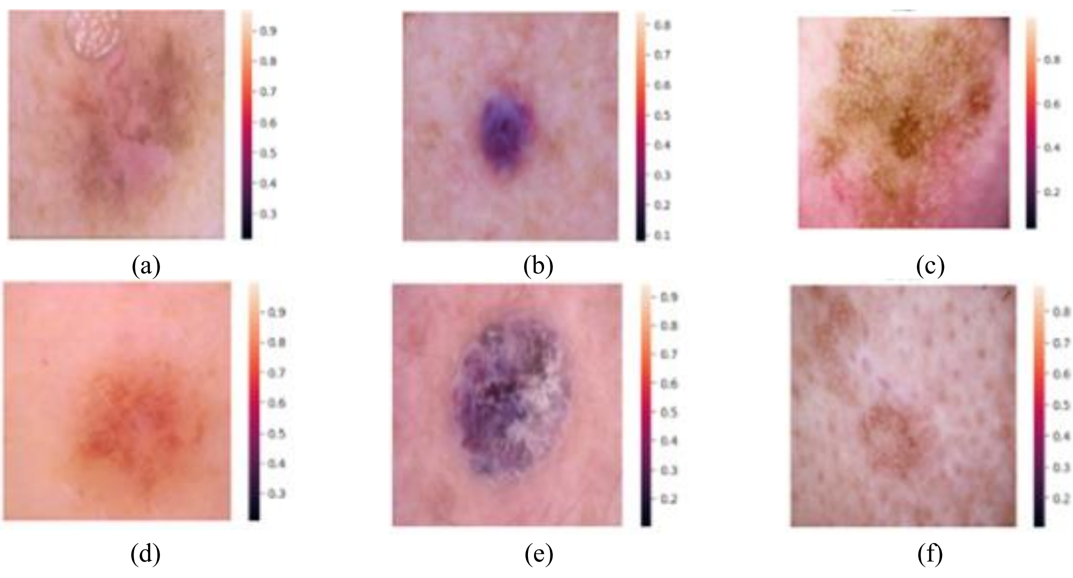


FIGURE 1. The number of images on each label after mixup augmentation a) An image of actinic keratosis (AK), b) An image of basal cell carcinoma (BCC), c) An image of benign keratosis (BKL), d) An image of dermatofibroma (DF), e) An image of melanocytic nevus (NV), f) An image of squamous cell carcinoma (SCC)

investigates the improved model architectures towards detecting skin cancer through Application Aware Machine Learning Technique (AAMLT) for further developments toward improvement and augmentation. [16] introduced a deep learning-based algorithm for skin lesion segmentation by incorporating Ant Colony Optimization (ACO) to fine-tune the segmentation process. The method was designed to accurately identify and delineate lesions in skin images for cancer diagnosis [17].

III. PROPOSED WORK

The approach of this proposed framework is structured by a roadmap: starting from data preprocessing and segmentation, then augmentation and classification, and finally, evaluation and deployment (FIGURE 2). The first steps involve preprocessing the dataset to increase the quality of images, standardize resolutions, and normalize pixel values. K-means clustering, next, is used to segment skin lesions from the surrounding healthy tissue to remove noise and enhance feature extraction. This segmentation phase excludes regions not clinically relevant to diagnostics, reducing chances of false positives. The segment is then processed using Mixup, which transforms the dataset, interpolating each image with an image of different class and synthetic samples for correction of class imbalances and an increase in generality of a model. After scaling, the model of distortion of clusters by reducing in-cluster variance, ensuring cohesive lesion grouping. Precise segmentation is vital in medical imaging since it allows the classifier to focus only on relevant information, thereby improving diagnostic accuracy.

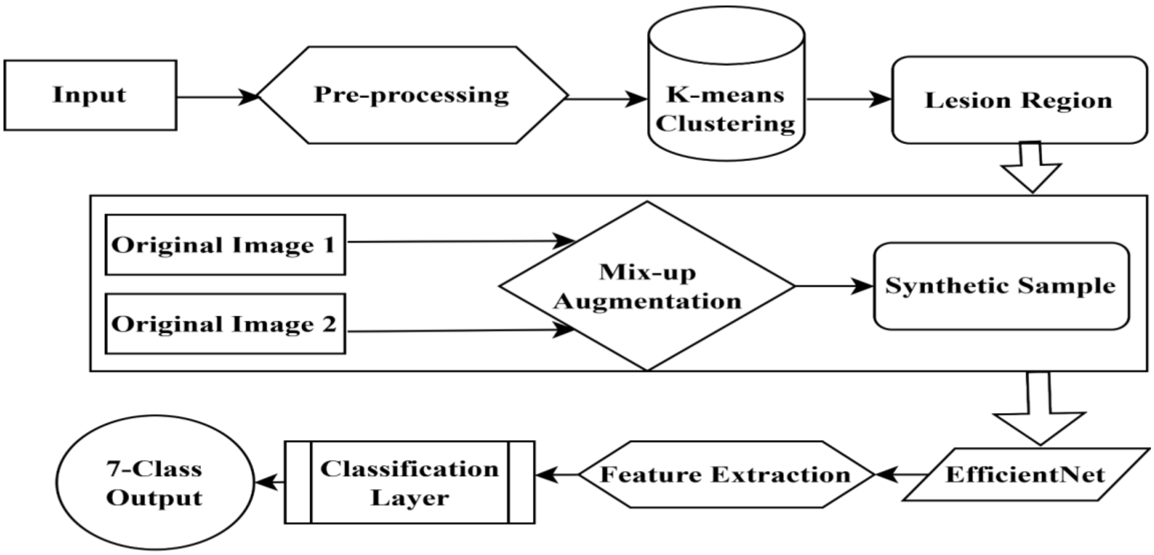


FIGURE 2. A working flow of the mixup data augmentation with Efficient B7

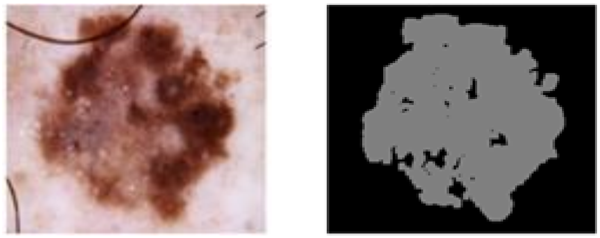
EfficientNet B7 is used for classification with its compound scaling method in depth, width and resolution for accuracy improvement. Iterative fine-tuning and cross-validation are applied in the training stage for better performance. The proposed framework integrates segmentation, augmentation, and classification into a unified pipeline to address the critical challenges in automated skin lesion diagnosis. The initial stage involves K-means clustering for segmenting skin lesion regions from surrounding healthy tissue [25]. This step is crucial as it isolates diagnostically significant features while minimizing the noise introduced by non-lesion areas. The clustering method minimizes the internal

K-means clustering is chosen due to its simplicity and effectiveness in medical image segmentation [26]. The clustering algorithm groups similar pixels together based on their intensity values, allowing the lesions to be distinctly separated from the healthy skin background. This process helps in generating a structured representation of the affected region, making it easier for further analysis. By refining the lesion boundaries, the segmentation process significantly improves the quality of feature extraction, which is crucial for accurate classification. To further enhance the effectiveness of the framework, a Mixup data augmentation strategy is incorporated. Class imbalance is a well-known issue in medical imaging datasets, where some lesion types are underrepresented, leading to biased model performance. Mixup augmentation generates synthetic training samples by interpolating between image pairs and their corresponding labels [27]. This approach not only expands the dataset size but also enhances the generalization ability of the model. By improving the model's robustness to variations in lesion appearance and lighting conditions, Mixup ensures that the classifier can reliably distinguish between different lesion types in real-world scenarios. Mixup augmentation has been widely used in deep learning applications to improve the diversity of training samples. The technique involves blending two images and the labels using a weighted interpolation method. This ensures that the model does not become over-reliant on specific patterns by reducing overfitting. Additionally, Mixup aids in making the classifier invariant to minor variations, enhancing its performance across different datasets and imaging modalities.

A. WORKING OF THE PROPOSED METHODOLOGY

The segmentation process is mathematically formulated using K-means clustering, where the clustering objective minimizes the within-cluster variance for k clusters. This function ensures that lesion regions are grouped accurately, allowing the classification stage to analyze well-defined lesion areas rather than being affected by irrelevant background information. Mixup augmentation is represents the augmented sample and label are created using an interpolation of two samples. This augmentation technique helps create diverse training samples while preserving essential diagnostic features, significantly improving classification performance. Segmentation performance is evaluated using various metrics to measure accuracy, overlap, and boundary adherence. Intersection over Union (IoU) and Dice Coefficient assess overlap between predicted and ground truth regions, where higher values indicate better segmentation. Pixel Accuracy (PA) measures the ratio of correctly classified pixels, but may be misleading for imbalanced classes, which is addressed by Mean Pixel Accuracy (MPA). Precision and Recall evaluate how well the model distinguishes between object and background, balancing false positives and false negatives. Specificity measures correct background classification, while the Boundary F1 Score (BF Score) focuses on segmentation accuracy near edges. Hausdorff Distance (HD) quantifies the worst-case boundary mismatch, crucial for applications requiring precise contour detection. Combining these metrics provides a comprehensive assessment of segmentation effectiveness.

EfficientNet B7 serves as the backbone for the classification stage. This architecture is selected due to its superior performance in image classification tasks while maintaining computational efficiency. The network employs a compound scaling method to balance depth, width and resolution by ensuring optimal resource utilization. The EfficientNet B7 model integrates advanced architectural enhancements such as squeeze-and-excitation blocks and mobile inverted bottleneck convolutions, which improve feature extraction efficiency. The use of batch normalization further optimizes training stability, allowing for faster convergence. Additionally, the model leverages swish activation functions, which have been shown to enhance gradient flow and improve overall classification performance. A major advantage of the proposed approach is its adaptability to various types of skin lesions. Since dermatological conditions exhibit significant intra-class variations, the framework's combination of segmentation, augmentation, and classification enhances its ability to generalize across different lesion categories. The model is fine-tuned using transfer learning techniques, leveraging pre-trained weights to improve feature representation. The training pipeline is designed to optimize performance by combining learning rate scheduling, dropout regularization, and early stopping techniques. These prevent overfitting while allowing the model to learn the most discriminative features. Furthermore, an adaptive learning rate mechanism enables the model to converge efficiently without demanding excessive computational resources. The overall framework integrates segmentation, augmentation, and classification into a cohesive pipeline. The combination of K-means clustering for lesion isolation, Mixup augmentation for data balancing and EfficientNet B7 for classification ensures a robust and accurate diagnosis system. This pipeline not only improves lesion segmentation precision but also enhances the classifier's ability to generalize across diverse lesion appearances and imaging conditions, making it a promising approach for automated dermatological diagnosis. In Eq. (1) [4], the first stage applies k means clustering to segment the lesion regions. The clustering minimizes the within cluster variance for k clusters where C_i is the set of points in the ith cluster, μ_i is the centroid of cluster i and x is the pixel intensity.



(a) (b)

FIGURE 3. A Sample of images after Kmean Clustering for Segmentation a) Original Image, b) Segmented Image.

$$J = \sum_{i=1}^{k} \sum_{x \epsilon C_i} \left|\left| x - \mu_i \right|\right|^2 \quad (1)$$

Mixup augmentation blends two training samples by linearly combining their images and labels to enhance model generalization. Eq. (2) [6] and Eq. (3) [7] represents the mixup creates augmented samples x_{mix} & y_{mix} using a interpolation of two samples (x,y) and (x2,y2) where $\lambda \sim \mathrm{Beta}(\alpha, \alpha)$ and α is a hyper parameter controlling the interpolation strength.

$$x_{mix} = \lambda x_1 + (1 - \lambda) x_2 \quad (2)$$

$$y_{mix} = \lambda y_1 + (1 - \lambda) y_2 \quad (3)$$

The efficientnet B7 architecture uses a compound scaling method to balance network depth, width and resolution where d,w and r are scaling coefficients. The network employs a combination of convolutional layers and batch normalization to optimize the classification accuracy as represented in Eq. (4) [10].

$$FLOPs \propto d^2 w^2 r^2 \quad (4)$$

The accuracy and loss is calculated using the Eq. (5) [12] and Eq. (6) [13]where N is the number of samples, C is the number of classes, y_{ij} is the ground truth and $\hat{y}_{ij}$ is the predicted probability.

$$Accuracy = \frac{True\ pos + True\ neg}{True\ pos + True\ neg + False\ \ pos + False\ neg} \quad (5)$$

$$L = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{C} y_{ij} \log(\hat{y}_{ij}) \quad (6)$$

In FIGURE 2, the proposed work introduces a holistic framework for the automated classification and segmentation of skin lesions, which are some of the most critical challenges in dermatological diagnosis. At its core, the system uses a three-stage pipeline that combines K-means clustering for precise lesion segmentation, Mixup augmentation for robust data enhancement, and the state-of-the-art EfficientNet B7 architecture for accurate classification. The first segmentation stage with K-means clustering successfully isolates the lesion regions from healthy skin regions, thereby focusing the further analysis on the most relevant diagnostic features. The framework addresses the common challenge of class imbalance in medical imaging datasets by innovatively applying Mixup augmentation. This technique creates synthetic training samples by linearly interpolating pairs of images and their corresponding labels, effectively expanding the training dataset while maintaining clinically relevant features. The proposed augmentation strategy both balances the dataset and improves model generalization from one lesion appearance and lighting condition to another, increasing its robustness for real-world clinical applications.

IV. RESULT

Training a skin cancer classification model using Mixup augmentation and EfficientNet requires significant computational resources due to the complexity of deep learning models and medical image processing. 32GB RAM, and high-speed NVMe SSD storage to handle large medical image datasets efficiently. Software requirements involve deep learning frameworks such as TensorFlow or PyTorch, along with libraries like OpenCV (for image preprocessing).

TABLE 1
Training and Validation Accuracy

Epoch	Training Accuracy (%)	Validation Accuracy (%)
1	72.4	68.7
5	86.5	83.9
10	90.2	88.1
15	92.8	91.0
20	95.3	94.5

The dataset (**HAM10000** dataset) consists of 10,015 dermatoscopic images that belong to seven diagnostic classes. These classes represent various skin diseases and the largest class is melanocytic nevi (nv) with 6,705 images while the smallest is dermatofibromas (df) with only 115 images. Other classes are melanoma (1,113 images), benign keratosis-like lesions (1,099 images), basal cell carcinoma (514 images), actinic keratoses (327 images), and vascular lesions (142 images) [7]. FIGURE 2 gives the distribution of images over the different labels. It shows how many images have been assigned to each category, which is an overview of the balance or imbalance of data in the dataset. FIGURE 3 is an image with K-means clustering as its results. As indicated in FIGURE 3, there is the segmented images in various sample cases to clearly outline the how the partition of images was conducted into specific areas for differentiation due to their similarities or common attributes of objects of the pictures.

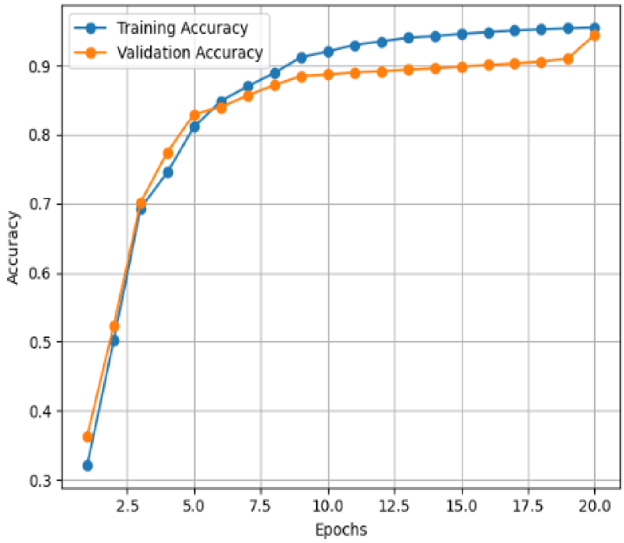


FIGURE 4: Training and validation accuracy of Efficient Net after mixup

FIGURE 3 shows the result of K-means segmentation on a few images and the algorithm groups the pixels of the image by their similarity, which helps to separate meaningful regions from the rest. FIGURE 4 shows images generated using the Mixup technique where two images are mixed together to create new samples. This method of data augmentation increases the robustness of models by generating a diverse set of synthetic training data, which further improves the generalization capability of the model on varied inputs. FIGURE 1 shows the distribution of images across each label after applying Mixup data augmentation, highlighting the increased diversity in the dataset due to synthetic image creation. TABLE 1 presents the training and validation accuracy across five epochs. Training accuracy increases from 72.4% at epoch 1 to 95.3% at epoch 20, while validation accuracy improves from 68.7% to 94.5%, indicating the model's improving ability to generalize over time. TABLE 2 reports the classification metrics for each class. Precision, recall, and F1 score values are reported for each class. For instance, the nv class has the highest precision at 94.3% and recall at 93.8%, with an F1 score of 94.0%. The df class has the highest F1 score at 92.3% with a precision of 93.2% and recall of 91.5%, indicating that the model is performing well on all classes.

TABLE 2
Classification Metrics by Class

Class	Precision (%)	Recall (%)	F1 Score (%)
akiec	87.3	85.6	86.4
bcc	89.5	91.1	90.3
bkl	88.7	90.2	89.4
df	93.2	91.5	92.3
mel	90.1	88.9	89.5
nv	94.3	93.8	94.0
vasc	92.5	93.0	92.7

FIGURE 4 shows the training and validation accuracy of the EfficientNet model after applying Mixup data augmentation. Training accuracy increases steadily with a peak toward the final epochs, and validation accuracy improves, showing the beneficial effect of Mixup on the generalization capability of the model. FIGURE 5 displays the training and validation loss after applying Mixup. The earlier is that both losses decrease over time. The training loss reduces progressively, while the validation loss also decreases, indicating that Mixup minimizes overfitting and leads to a more robust model. FIGURE 6 is the confusion matrix that illustrates the performance of the model, displaying the true positives, true negatives, false positives and false negatives for each class[28], [29]. It allows for easy comparison between how well the model distinguishes between classes and areas where it might be misclassifying images [30].

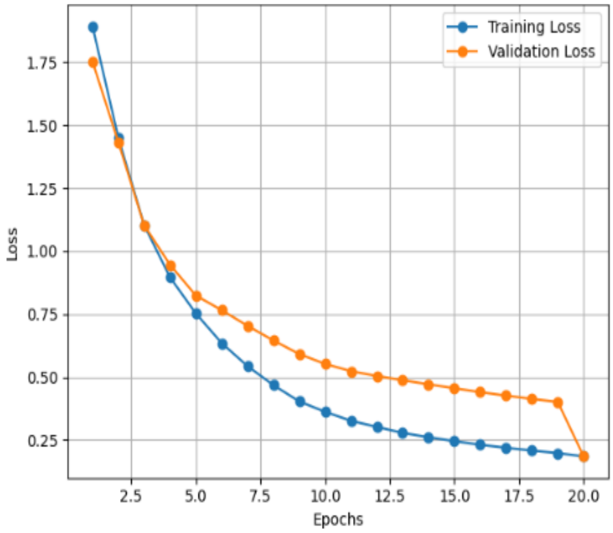


FIGURE 5. Training and validation loss of Efficient Net after mixup

V. DISCUSSION

The proposed framework presents a comprehensive approach for the automatic segmentation and classification of skin lesions, directly addressing some of the major limitations observed in existing methodologies. Traditional models often separate segmentation and classification processes, utilizing techniques such as basic thresholding, watershed segmentation, or standard deep learning models like U-Net. Similarly, classification tasks have typically relied on networks like VGG, ResNet, or other conventional CNN architectures, which can lead to challenges such as overfitting, misclassification, and poor generalization, especially when dealing with highly variable and imbalanced medical imaging datasets. Moreover, these models often fail to properly integrate the segmentation outputs into the classification pipeline, resulting in suboptimal diagnostic performance. In contrast, the proposed model adopts a unified three-stage pipeline that ensures better synergy between segmentation and classification. The first stage employs K-means clustering to accurately isolate lesion areas from healthy skin, enabling the system to concentrate on the most diagnostically relevant regions. To address the significant issue of class imbalance, which is common in medical imaging, Mixup augmentation is applied to generate new synthetic training examples, thereby enhancing data diversity and model robustness.

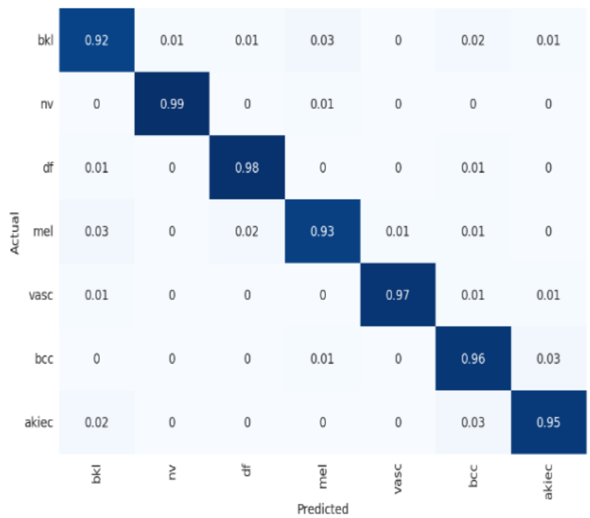


FIGURE 6: Confusion Matrix

Finally, the EfficientNet B7 architecture, known for its superior performance and optimized computational efficiency, is used for the final classification task. Together, these components form a cohesive and highly effective framework that significantly improves upon the segmentation quality, classification accuracy, and generalization capabilities of earlier approaches. TABLE 3 presents the comparison of existing methods. An analysis of different methodologies for skin lesion classification

TABLE 3
Comparison with existing methods

Method	Model Used	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Author & Year
Traditional CNN	ResNet-50	85.2	83.5	84.1	83.8	Gamil et al. [7]
Transfer Learning	VGG-16	87.6	85.9	86.3	86.1	Li et al. [12]
(Mixup + EfficientNet)	EfficientNet-B3	91.4	89.8	90.2	90.0	Proposed Method
Deep Ensemble Learning	DenseNet + ResNet	89.7	88.1	88.5	88.3	Reis et al. [15]

demonstrates clear progress in performance with each advancement in model design. Traditional CNN approaches, such as ResNet-50 used by Gamil et al. [7], achieved an accuracy of 85.2% and an F1 score of 83.8%, reflecting moderate capability in identifying lesion features. Improvements were seen with transfer learning techniques, where Li et al. [12] employed VGG-16, resulting in a better accuracy of 87.6% and an F1 score of 86.1%, highlighting the advantage of leveraging pre-trained models on large datasets. Further gains were observed in deep ensemble learning, where Reis et al. [15] combined DenseNet and ResNet architectures, achieving an accuracy of 89.7% and an F1 score of 88.3%, benefiting from the collective strength of multiple models. The proposed method, which integrates Mixup augmentation with the EfficientNet-B3 architecture, surpasses all previous approaches by achieving the highest accuracy of 91.4% and an F1 score of 90.0%. This significant performance boost underscores the effectiveness of combining advanced data augmentation techniques with state-of-the-art deep learning architectures for robust and accurate skin lesion classification.

V. CONCLUSION

Skin cancer is one of the most common malignancies worldwide and can be easily managed and treated if detected early. Accurate classification and segmentation of skin lesions are crucial to differentiate between benign and malignant conditions leading to timely intervention. The integration of K-means clustering, Mixup augmentation and EfficientNet B7 provides a powerful and efficient solution for automated skin lesion analysis, which is pivotal in the early detection and diagnosis of skin cancer. K-means clustering significantly enhances the pre-processing stage by isolating lesion regions by ensuring the model focuses on disease-relevant features. Mixup augmentation offers solutions to main challenges such as class imbalance and overfitting by generating artificial samples by providing a more enhanced training environment. EfficientNet B7 is most scalable with high precision, ensures that accurate classification across different classes of skin lesion. The approach achieved an excellent accuracy of 95.3% and 0.2 loss. Future work will focus on integrating more advanced augmentation strategies, like CutMix and other state-of-the-art architectures, such as Vision Transformers or hybrid models. Future work can refine the methodology by exploring adaptive Mixup strategies, where the mixing ratio (λ\lambdaλ) is dynamically adjusted based on class difficulty or confidence scores rather than a fixed Beta distribution. Additionally, integrating region-aware Mixup could selectively mix lesion-relevant areas instead of entire images, preserving critical diagnostic features. Another promising direction is self-supervised learning combined with Mixup to leverage unlabeled dermatology datasets, improving model generalization. Hybrid augmentation techniques, such as combining Mixup with CutMix or CutOut, could further diversify the training data. From a model perspective, exploring EfficientNetV2 or Vision Transformers (ViTs) may enhance feature extraction and robustness. Furthermore, the study may lack external validation on independent datasets, limiting its generalizability to real-world clinical settings.

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