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Enhancing Oral Squamous Cell Carcinoma Detection using EfficientNetB3 from Histopathologic Images

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***Abstract*—Oral Squamous Cell Carcinoma (OSCC) is a highly aggressive and prevalent form of oral cancer, accounting for over 90% of cases globally. Early detection of OSCC is vital since early-stage diagnosis offers a five-year survival probability of about 80%, therefore significantly raising patient survival rates. Conversely, standard diagnostic methods based on histological analysis demand highly qualified experts, are time-consuming and are prone to human error. This work addresses these issues by exploring the application of deep learning to identify OSCC using histopathologic images automatically. The work uses a dataset split into OSCC and Normal classes, including 5,192 images. The EfficientNetB3 model is trained and tested on this dataset, utilizing a 70:15:15 split for training, validation, and testing. Using data augmentation techniques utilized to enhance the model, key measures, including accuracy, precision, recall, and F1-score, serve to evaluate its performance. On the test set, the model showed the ability to accurately identify OSCC and healthy tissues with a precision of 0.98, recall of 0.98, and an F1-score of 0.98. A final accuracy of 98% was obtained. These findings suggest that the proposed method offers a practical substitute for early, automated OSCC identification, improving patient outcomes and diagnostic accuracy in clinical settings.**

Keywords— Oral Squamous Cell Carcinoma, OSCC, Deep Learning, EfficientNetB3, Histopathologic Image Classification, Early Detection, Convolutional Neural Networks (CNNs), Automated Cancer Detection, Medical Image Analysis.

I. INTRODUCTION

1.1 Background and Context

Oral Squamous Cell Carcinoma (OSCC) is one of the most aggressive and prevalent forms of cancer, accounting for more than 90% of all oral cancer cases globally. Beginning in the squamous cells covering the mucosal surfaces of the oral cavity, OSCC causes substantial health risks, including death if not identified early, deformity, and metastasis. With OSCC's main cause of oral cancer-related death, the World Health Organisation (WHO) ranks oral cancer among the top 10 most common malignancies globally. Particularly in Southeast Asia, OSCC is very widespread in regions where tobacco, alcohol, and betel quid are used extensively. This major healthcare issue underlines the need for early diagnosis to increase patient survival rates and reduce treatment intensity [1].

Conventional OSCC diagnosis methods are used in clinical exams, followed by biopsy and histological analysis. Though exact, these methods are labor-intensive, time-consuming, and primarily dependent on specific knowledge. In resource-limited environments, a lack of competent pathologists aggravates this issue and occasionally leads to delayed or inaccurate diagnosis [2]. In this sense, advances in artificial intelligence (AI) and deep learning (DL) present fascinating routes to increase diagnosis accuracy and efficiency in OSCC identification from histology images. Deep learning, especially by convolutional neural networks, has revolutionized medical picture analysis. CNNs have outperformed traditional machine learning methods in applications involving disease detection, particularly in breast cancer, diabetic retinopathy, and melanoma [3]. Transfer learning, the application of pre-trained models to new tasks, has also been beneficial in enhancing performance, especially when training data is limited. Since the modern model EfficientNet has demonstrated great promise in balancing computational efficiency with high accuracy, it is an ideal option for medical image classification activities, including OSCC detection. OSCC detection deep learning integration offers the ability to make rapid, automated, correct diagnoses, therefore reducing the necessity for hand histological evaluations. Still, in its early stages in OSCC diagnosis, deep learning requires further research and validation to ensure clinical relevance despite these advances. This work aims to close this disparity using EfficientNetB3 architecture to detect OSCC from histopathologic images, thereby advancing AI-driven detection tools for oral cancer [4].

1.2 Problem Statement

Early oral squamous cell cancer diagnosis determines how likely survival is to improve. Still, most current diagnostic techniques depend on histological analysis, that is, hand-eye under a microscope study of biopsy samples. Although effective, this method has major limitations. It is time-consuming and labor-intensive; it calls for qualified pathologists who might need more resources to be readily available in settings with limited resources [5]. Moreover, personal interpretation of the diagnostic process renders humans error-prone so that conflicting treatment recommendations could follow from differences in diagnosis findings. The worldwide rise in OSCC cases matches the demand for more exact, consistent, and effective diagnostic tools. Large medical imaging datasets and developments in computer capacity offer an opportunity to build automated systems that either assist or even replace human diagnostic processes [6]. For deep learning methods, especially those incorporating CNNs, medical picture analysis has shown considerable potential. Reaching diagnostic accuracy on par with human experts will depend on teaching these models to identify OSCC-related trends in histology images.

Nevertheless, current models often suffer from overfitting, low generalisability over datasets, and lack of interpretability [7]. The fundamental problem this work aims to address is the building of an accurate, generalizable, and inexpensive deep-learning model for OSCC recognition from histopathologic images. Automating the detection process and improving diagnosis outcomes using modern CNN architectures such as EfficientNetB3 aids the research to exceed the constraints of current diagnostic procedures [8].

1.3 Relevance of the Topic

Early detection of OSCC is critically important due to its aggressive nature. Patients diagnosed in the early stages of OSCC have an estimated 80% five-year survival rate; late-stage diagnosis yields a survival rate of less than 20%. Early detection also reduces the need for intrusive, disfiguring treatments like major surgery, which could drastically compromise a patient's quality of life. Consequently, the improvement of diagnosis methods determines the improved patient outcomes in OSCC [9]. The application of deep learning in OSCC detection is rather pertinent since it offers more consistent and reliable diagnosis results, therefore relieving medical practitioners of some burden. Driven by deep learning, automated solutions can have considerable benefits by minimizing human error, standardizing diagnosis outcomes, and providing speedy assessments even in places with limited access to skilled medical staff [10]. Furthermore, the development of models like EfficientNetB3, which strikes a mix between computational correctness and efficiency, has further effects on medical imaging and diagnostics. This work supports the ongoing efforts to improve diagnosis accuracy and efficiency since it fits the global trend of adding artificial intelligence into medical systems. By raising the application of deep learning in recognizing OSCC, this work supports the change towards more democratized and accessible healthcare solutions [11].

1.4 Objectives of the Research

The main goal of this work is to build and assess a deep learning-based model based on EfficientNetB3 architecture to identify OSCC from histological images. By using transfer learning and fine-tuning approaches to increase diagnosis accuracy while preserving computational economy, the project seeks to surpass the restrictions of conventional diagnostic approaches. Preprocessing the dataset is a major concentration of this work since it guarantees that images are enhanced, scaled, and normalized to raise the generalization capacity of the model over several datasets. Particularly when dataset sizes are small, data augmentation methods are used to reduce overfitting and improve the robustness of the model. Using important criteria, including accuracy, precision, recall, and F1-score, the study seeks to assess the performance of the model as well. These performance metrics can help one understand how well the EfficientNetB3 model performs relative to other designs, such as ResNet and VGG. Furthermore, interpretability methods are included in the study to depict the decision-making process of the model, providing a more open and understandable method of deep learning for practical use. The final aim is to provide an automated OSCC diagnosis scalable, practical solution.

II. LITERATURE REVIEW

Rahman et al. (2022) explored deep learning techniques for oral cancer detection using the AlexNet Convolutional Neural Network (CNN) on OSCC biopsy images. The study aimed to examine the flaws in traditional biopsy methods, which depend on human error in differentiating cancerous cells. By means of transfer learning, the proposed model found relevant characteristics from OSCC images and achieved a classification accuracy of 97.66% for training and 90.06% for testing. These results reveal how well deep learning could minimize human error, increase diagnosis accuracy, and improve early identification of oral cancer [13].

Redie et al. (2023) investigated deep-learning techniques for oral cancer detection using histopathology images. Analyzing ten pre-trained convolutional neural networks (CNN) models with an eye towards a transfer learning approach to detect normal and OSCC tissues, VGG19 achieves the best accuracy—96.26%—by use of data augmentation. The authors also proposed a hybrid of VGG19 with a unique naïve inception block to overcome vanishing gradient and computation challenges. Showing its ability to improve oral cancer detection accuracy and efficiency in clinical environments, the block-wise fine-tuned model outperformed previous approaches [14].

Maia et al. (2023) examined the usage of deep learning models for the diagnosis of dysplasia and oral squamous cell cancer (OSCC) using a freshly produced dataset P-NDB-UFES. This dataset has 3,643 histological image patches categorized as OSCC, dysplasia, and non-dysplasia. The investigation assessed convolutional neural networks (CNNs), transformer models, and few-shot learning methods (Siamese, Triplet, and ProtoNet) for classification. Reportedly reaching the best-balanced accuracy (91.91%), recall, and precision was DenseNet-121. Few-shot learning methods proved less successful; statistical variations were based on model configurations and optimizers.

Sultana et al. (2023) investigated early-stage oral cancer using a deep-learning architecture built on a modified CNN. The study uses a set of 8,000 histology images equally divided into two groups of oral tumors. The study underscored the possibility of histopathology datasets to significantly affect medical research by offering perfect and rapid data pattern detection. Over more than thirty epochs, the CNN model exhibited the promise of the framework for early-stage diagnosis and surpassed other current techniques with its best accuracy of 97.6% [16].

Lin et al. (2021) presented a smartphone-based imaging diagnosis method for detecting oral cancer using deep learning algorithms. They created a medium-sized oral dataset with five disease categories using a centered image-capturing technique. By resampling photos to lower uncertainty from smartphone cameras, the study may evaluate a High-Resolution Network's (HRNet) cancer detection accuracy. The method was obtained with a sensitivity of 83.0%, specificity of 96.6%, accuracy of 84.3%, and F1 score of 83.6%. HRNet outperformed VGG16, ResNet50, and DenseNet 169, which showed promise for primary oral cancer diagnosis [17].

Jeyaraj et al. (2019) developed a deep-learning algorithm for the early identification and classification of oral cancer using hyperspectral imaging. Two layers of their separated convolutional neural network (CNN) were meant to classify malignant tumors and identify benign and normal tissues. With a sensitivity of 0.94 and a specificity of 0.91, the method obtained a classification accuracy of 91.4%. A 500 training pattern expanded dataset obtained 94.5% accuracy. The partitioned CNN improved diagnostic quality, according to the

study, above traditional medical image classification methods [18].

III. METHODOLOGY

This section provides a detailed description of the dataset, data augmentation techniques, model architecture, and the proposed work to develop and evaluate the EfficientNetB3 model for Oral Squamous Cell Carcinoma (OSCC) detection, as illustrated in Figure 1.

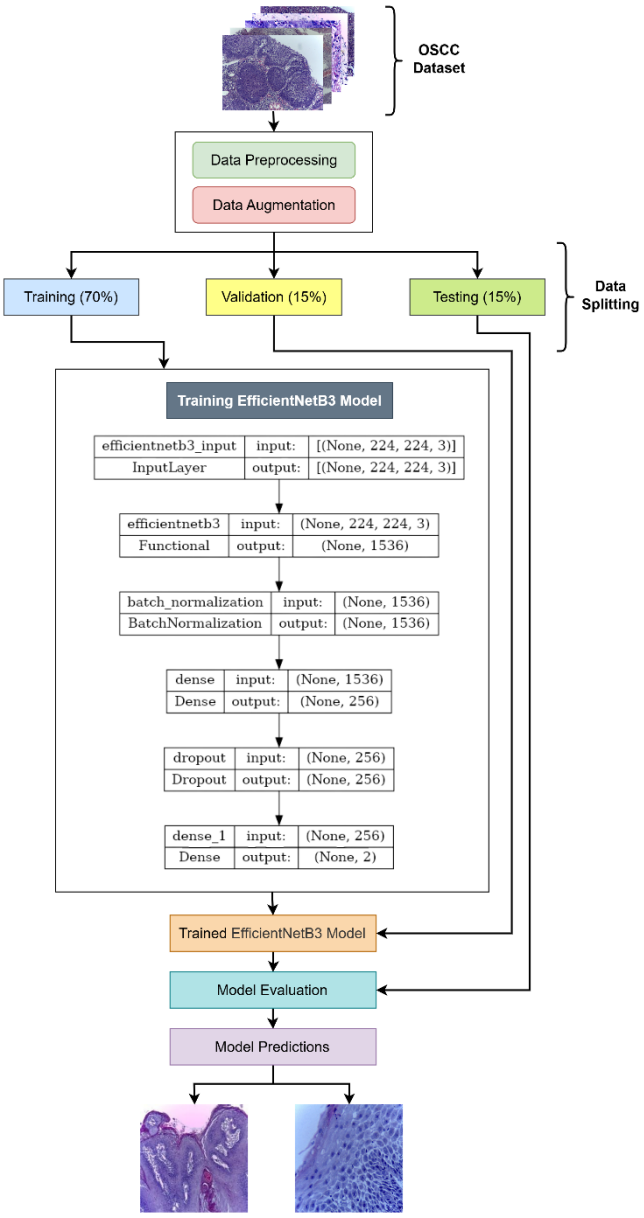

Fig. 1. Proposed Methodology

A. Dataset Description

The dataset used for this study is sourced from a Kaggle repository [19] and consists of histopathologic images categorized into two classes: normal and oral squamous cell carcinoma (OSCC). Training, validation, and testing sets separating the 5,192 images in the dataset guarantee a fair and complete evaluation of the model. Figure 2 demonstrates that the OSCC class consists of 2,698 photos showing malignant tissues impacted by oral squamous cell carcinoma; the Normal class consists of 2,494 images showing healthy oral tissues. This almost equal representation of both classes enables an objective training procedure in which the model gains the effective capacity to discriminate between benign and malignant tissues.

The dataset is partitioned in a 70%-15%-15% ratio to allow model training and evaluation, as illustrated in Figure 3. There are 3,634 photos in the training set; 1,775 falls in the Normal class, and 1,859 falls in the OSCC class). This forms the deep learning model, which might identify pertinent patterns and characteristics. Applied to change hyperparameters and track the performance of the model during training, the 779 validation set photos total 359 normal and 420 OSCC images. The testing set consists of 779 photos overall, 360 normal, and 419 OSCC images at finish. Acting as a separate dataset to assess the performance of the model on unprocessed data guarantees the generalisability of the results.

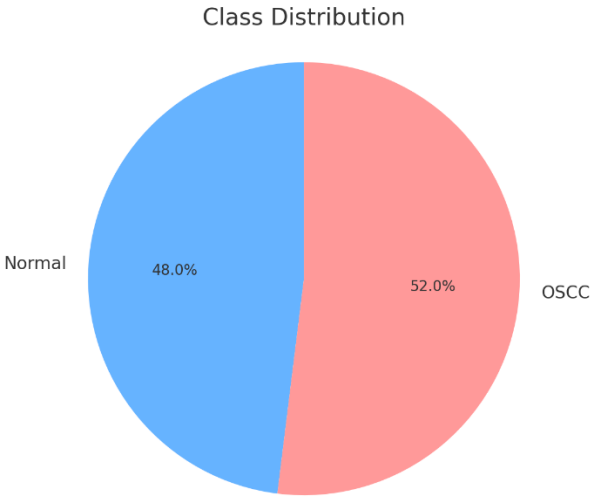

Fig. 2. Class Distribution.

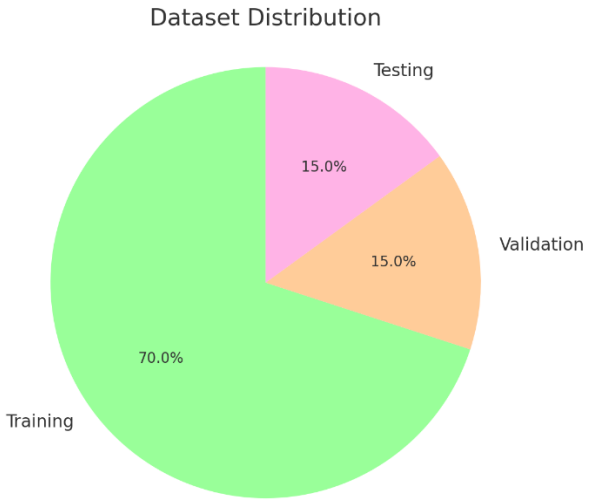

Fig. 3. Dataset Distribution.

The composition of the dataset guarantees that the deep learning model may efficiently train from the data and provide dependable predictions when applied in clinical situations for automated OSCC detection by means of almost balanced classes and proper splitting.

TABLE I. CLASS DISTRIBUTION OF IMAGES IN THE DATASET.

Class	*Total Images*	*Training Set*	*Validation Set*	*Testing Set*
Normal	2,494	1,775	359	360
OSCC	2,698	1,859	420	419

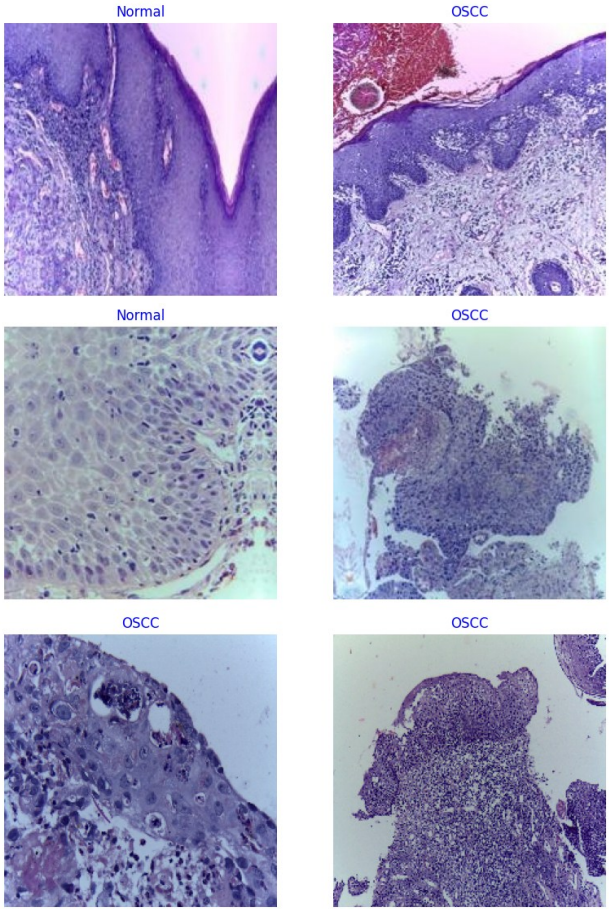

Fig. 4. Dataset Representation.

B. Data Augmentation and preprocessing

Data augmentation and preprocessing are crucial steps in Data augmentation, and preprocessing is essential for preparing the dataset for optimal performance of a deep-learning model. This approach avoids overfitting by artificially expanding the amount and variety of the dataset via different augmentation techniques, hence enabling better generalization of the model. These techniques randomly flip the images to provide variation in the angle of the images, therefore allowing the model to learn properties from multiple orientations and rotation by up to 20 degrees. By zooming (up to 20%), variations in image size are replicated, thereby ensuring that the algorithm learns to identify traits independent of scale. Moreover, variations in brightness and contrast help the model to match images taken under different lighting.

For preprocessing, which is necessary for EfficientNetB3 and provides consistency over the dataset, all images are shrunk to a standard input size of 224x224 pixels. Since it reduces the range of values the network must manage, normalizing the pixel values to a range of [0, 1] efficiently trains the model. While pretreatment pipelines guarantee that the model is trained on consistent, high-quality input data, augmentation helps the model become more resilient and able to generalize to new, unseen data.

C. Model Architecture

The cornerstone of the model architecture used in this work is EfficientNetB3, a state-of-the-art convolutional neural network developed for effective scalability and optimal performance in image categorization activities. EfficientNet B3 was selected and ideal for medical imaging uses needing exceptional precision since it could balance accuracy and computing efficiency. The model takes advantage of transfer learning; ImageNet pre-trained weights offer a strong basis for feature extraction from histology images. Custom layers on top of the EfficientNetB3 base enable the enhancement of the binary classification between the Normal and OSCC class capacity of the model. These customized layers consist of a dense layer with 256 neurons using the ReLU activation function to capture complex patterns in the input, dropout layers with a dropout rate of 0.45 to prevent overfitting, and a batch normalization layer to stabilize and expedite the training process. Each class's probability is generated eventually using a softmax layer. The model is trained using a learning rate of 0.001 and an Adamax optimizer; early stopping is applied to cease training should the validation loss stop improving. This design offers accurate, reliable, and efficient classification of OSCC; thus, its clinical uses are suitable.

D. Proposed Work

This work aims to detect oral squamous cell carcinoma (OSCC) by utilizing histopathologic images through an automated approach leveraging deep learning techniques. Constructed on the well-known EfficientNetB3 architecture, noted for its outstanding image classification task accuracy and efficient scalability, the Main focus of the work is on using transfer learning to improve this pre-trained model for binary classification between Normal and OSCC classes. Fundamental to the intended task is the implementation of data augmentation techniques to increase the variety of the dataset and prevent overfitting. Consistent input size and normalization guaranteed by preprocessing the dataset assure improved generalizing capacity of the model over several data.

During the training process, the performance of the model is monitored using validation criteria, including accuracy, precision, recall, and F1 score. Among regularisation techniques, dropout and batch normalization are applied, among others, to increase generality even further. Analyzing the model on a last-phase test set assures its performance on unprocessed data. Furthermore included are interpretability techniques to show the model's decision-making process, providing insight into which image components most influence the predictions. This proposed method is expected to be very important for the field of automated OSCC detection, thereby improving clinical diagnosis accuracy and efficiency.

IV. RESULTS AND DISCUSSION

This study thoroughly evaluates the EfficientNetB3 model's performance in classifying Oral Squamous Cell Carcinoma (OSCC) from histopathologic images, focusing on key criteria such as accuracy and loss plots, confusion matrix, and performance metrics to assess its effectiveness.

A. Accuracy and Loss plots

As Figure 5 illustrates, the model's accuracy rises constantly throughout training. Starting with the first epoch at 78.26%, the training accuracy increases rapidly as the model

develops the capacity to separate the Normal from OSCC classes. Training accuracy climbs to 97.52% by the tenth epoch and surpasses 98.57% after twenty epochs, therefore demonstrating effective learning. Starting at 89.22% in the first epoch and rising to 96.53% in the 20th epoch, the validation accuracy follows a similar trajectory. Regular validation accuracy of between 96 and 98% points to robust generalization on unprocessed data over the training phase. The concurrent rise in training and validation accuracy speaks to effective model learning free from clear overfitting.

As Figure 6 shows, the loss plot supports the model's learning advancement even more. Beginning in the first epoch at a high of 5.8987, the training loss mirrors the model's initial error rate. But it declines sharply with every epoch; by the tenth, it is 0.4553 and continues to drop until around the forty-first epoch. Starting at 4.1276 and dropping to 0.4602 in the tenth epoch, the validation loss follows a similar pattern. Both losses remain small and closely spaced during training, implying robust model generalization and low overfitting, hence validating the quality of the chosen architecture.

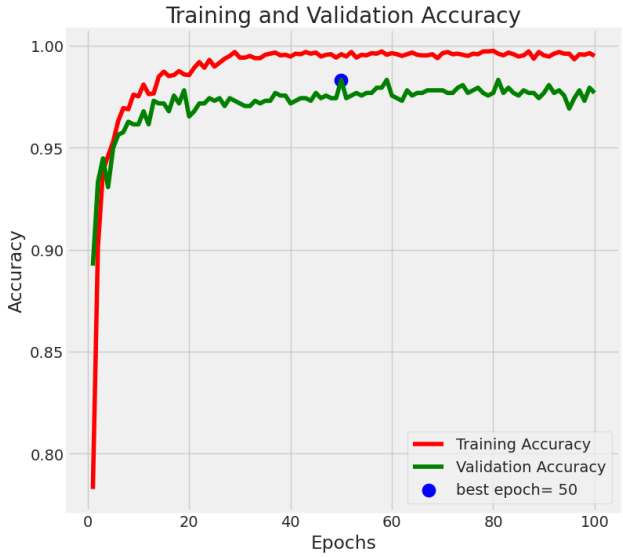

Fig. 5. Training and Validation Accuracy

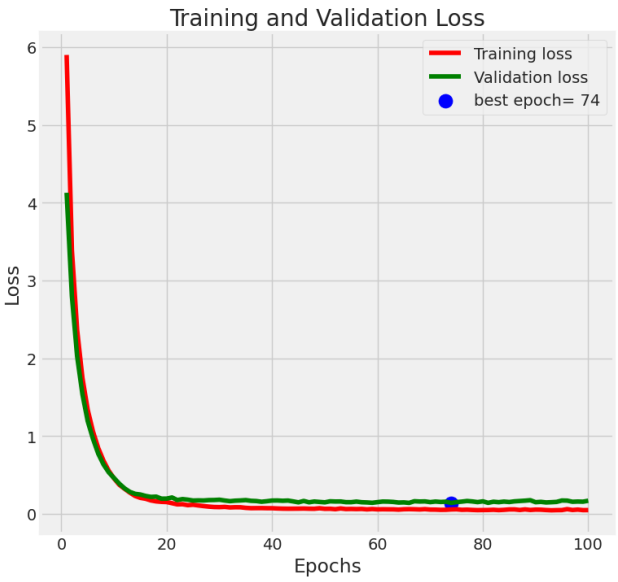

Fig. 6. Training and Validation Loss

B. *Confusion matrix:*

Presenting in Figure 7, the confusion matrix provides an insightful analysis of the performance of the model in categorizing "Normal" and OSCC (Oral Squamous Cell Carcinoma) samples. The matrix consists of four quadrants corresponding to the predicted labels on the horizontal axis and the real labels on the vertical axis. The correct model predictions are reflected by the matrix's (356 and 410) diagonal components. Especially by correctly classifying 56 "Normal" samples and 410 OSCC samples, the model shows outstanding prediction power.

The off-diagonal features attract emphasis to the misclassifications. In this case, the model mistakenly projected four cases of "Normal" samples as OSCC and misclassified nine OSCC samples as "Normal". This indicates that the model is really good at separating the two classes, as seen by a very low false positive rate (misclassifying normal as OSCC) and false negative rate (misclassifying OSCC as normal).

Generally speaking, the confusion matrix reveals that the model achieves high accuracy—especially in determining the OSCC scenarios with low error rates. The small number of misclassifications suggests that additional data augmentation techniques or hyperparameter fine-tuning could considerably enhance performance even more. This degree of accuracy is remarkable for therapeutic purposes, as early-stage OSCC identification can significantly affect patient outcomes.

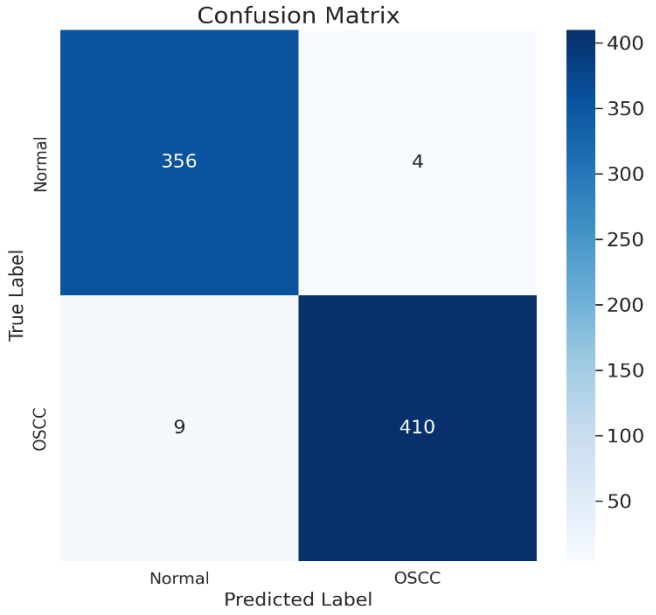

Fig. 7. Confusion matrix

C. *Performance Parameters:*

Table 2 presents, assessed by significant classification criteria, the performance parameters of the very promising proposed OSCC detection model. With a precision of 0.98, the "Normal" class indicates that 98% of the forecasts classified as such were accurate. Comparatively, the "OSCC" class's accuracy of 0.99 shows the model's strong capacity to recognize OSCC circumstances exactly.

Recall-wise, the model scored 0.99 for the "Normal" class, so accurately identifying 99% of all actual "Normal" samples; the recall for the "OSCC" class is 0.98, thus accurately classifying 98% of all actual OSCC samples. The F1-score, which balances accuracy and recall, is 0.98 for both the

"Normal" and "OSCC" classes, therefore demonstrating that the model maintains a reasonable degree of consistency between recognizing positive cases and minimizing false positives.

With 98% of all the data correctly identified by the model, its general accuracy across both classes is 98%. While the macro average for precision, recall, and F1-score is 0.98, which shows balanced performance across both classes, the weighted average of 0.98 accounts for the class distribution and hence increases the dependability of the model. These results, reported in Table II, highlight both the possible therapeutic applications and the effectiveness of the model for OSCC identification.

TABLE II. PERFORMANCE PARAMETERS

Class	*Precision*	*Recall*	*F1-Score*	*Accuracy*
Normal	0.98	0.99	0.98	0.98
OSCC	0.99	0.98	0.98	

D. Model Prediction and Results Visualization:

The EfficientNetB3 model's predictions were evaluated by loading a sample image and classifying it as either 'Normal' or 'Oral Cancer.' The input image went through the model for classification, following preprocessing and scaling to fit the model's input criteria. The expected label was shown alongside the input image, enabling visual interpretation based on model output. Said to be a "predicted mouse," Figure 8 shows the intended result. This highlights how effectively the model can detect images, therefore demonstrating its worth in clinical settings for the diagnosis of oral squamous cell cancer (OSCC). This approach strengthens the case for adding deep learning models, such as EfficientNetB3, into diagnostic processes where rapid and accurate predictions can improve patient outcomes by displaying how the model interprets and labels medical images.

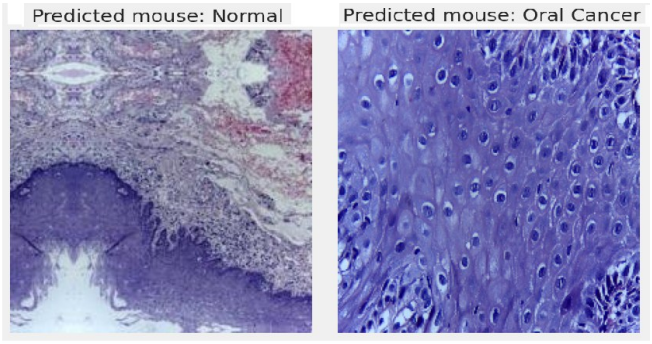

Fig. 8. Predicted result visualization

V. CONCLUSION

The study addresses the main difficulty of oral squamous cell cancer (OSCC) detection using deep learning techniques. Early, accurate OSCC diagnosis determines both lowering death rates and improving patient outcomes. Leveraging the EfficientNetB3 model, a powerful image classification system was developed using histopathologic images of OSCC and normal tissues coupled with intense data preparation and augmentation techniques. All told, there were 5252 images split into training, validation, and testing subsets. Showing an overall accuracy of 98% and a precision of 0.99 for the OSCC class and a recall of 0.98, the model demonstrated outstanding performance. Table 2 illustrates that, in discriminating between normal and cancerous cells, the F1-score, accuracy, and recall measures all routinely averaged around 0.98, hence verifying the reliability of the model. EffectiveNetB3 paired with data augmentation techniques was demonstrated to be successful in enhancing the generalizing capacity of the model and decreasing classification errors. The low false positive and false negative rates draw attention to the concept's pragmatic usefulness. Lastly, our work highlights the ability of advanced deep learning techniques to significantly increase OSCC detection, offering a valuable tool for enabling pathologists to make accurate diagnoses and hence aid in improving patient care and outcomes.

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