Analysis Of Supervised Learning Approaches For Identification Of Oral Squamous Cell Carcinoma: A Multimodal Approach

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Abstract. This research focuses on the early detection of Oral Squamous Cell Carcinoma by using a multi-modal approach: putting together features from histopathological images and clinical data. The proposed study has used 237 histopathological images classified as OSCC, leukoplakia with dysplasia, and leukoplakia without dysplasia, along with their respective clinical-demographic in- formation. It proposed several image classification supervised machine learning methods: the support vector machine, KNN, Decision Trees, Random Forest, Logistic Regression, Naive Bayes, taking ResNet50 features extracted from images. For KNN, the highest observed accuracy was 89%, while for linear SVM, the accuracy was 81%. Decision Trees and Random Forests overfitted in this case, whereas the Logistic Regression model presented rather balanced results. It thus evidences the potentiality of machine learning and multimodal data for the development of precise and cost-effective diagnostic tools in oral pathology, while among the optimal algorithms, KNN and linear SVM will be identified.

Keywords: Multimodal, Supervised methods, Oral Cancer, Histopathological images.

1 Introduction

Cancer starts when the cells in our body change and begin to spread uncontrollably. Usually, cells grow and divide when our body needs them and die when they are no longer needed by our body. Cancer cells are different from normal body cells as they keep growing even when our body doesn't need them. These abnormal growths of cells form a mass or a lump called tumor and can attack the nearby tissues or spread across other parts of the body. Oral cancer is one of the most common types of cancer worldwide affecting parts of mouth, tongue or lips [1]. The Worldwide index of oral cavity cancer is approximately 377713 new cases and 177757 deaths in 2020. It is more common in men and older people as compared to women [2]. Due to lack of resources and technologies early detection is difficult. More often, this disease is detected after the cancer has already started to spread i.e. the early stage which has 5 to 6 years of survival rate which is approx. 69.5%. However, in the later stage the rate drops to 31.6% [3]. In order to diagnose this disease, specialized doctors and specialists need to perform various practices and tests that includes collection of tissue cells, enquiring patient's medical records such as name, gender, age, weight, consumption of any kind of tobacco and alcohol, effected areas and size of the tumor [4].

Advancement in technology has enhanced the process of early detection and diagnosis of this disease. Machine learning algorithms demonstrated high performance in identifying cancerous lesions from histopathological images. These methods not only reduce the workload on physicians but also help to improve diagnostic precision by analyzing large datasets and recognizing patterns which might get missed by the human eye [5]. In this paper we focus on various supervised machine learning algorithms such as SVM, decision tree, random forest, Naïve bias, KNN and logistic regression for medical diagnosis. Doctors and specialists utilize both traditional and advanced methods to detect cancer at an early stage. Hence, this research combines both medical aspects and technology to come up with promising and efficient results. This research is based on multimodal approach as it combined both histopathological images along with clinical data of the patients to get better generalization capability. Furthermore, there is a detailed explanation about our research and implementation categorized in various sections. Section 2 provides some collective studies which were carried out during the past few years and how technology plays an important role in medical diagnosis. All this research work has motivated us to bring off this project as it was interesting to know that several branches of science and technologies can be merged together to conclude with a lifesaving achievement. Next, we have section 3 providing a detailed description of the dataset used for this research, methodologies used and the multimodal architecture. Lastly, we have the results and conclusion in section 4 which provides a detailed explanation about progress and achievements.

2. Literature review

Several studies have been carried out in the coming years providing promising results in the field of diagnosis of oral cancer using histopathological images. This section provides a rigorous investigation into some of the studies conducted so far, it provides a collective analysis about how researchers are investing their time and knowledge to come up with early detection of oral cancer. With OSCC being a global burden and a high mortality disease, the accurate early diagnosing of the disease has become a chal- lenge. Different strategies tapping into the application of ML and DL have been suggested in order to improve diagnostic consistency and speed. Such an approach com- bines explainability techniques with low-power histopathological image analysis in diagnosing SCCs in various organs. By proposing an ensemble feature selection-based CatBoost classifier, high accuracy, 93.43% of public cohort and 96.66% of multi-center private datasets were obtained. ELI5, LIME and SHAP are tools, which helped to ex- plain model and supported healthcare professionals in making decisions [5]. In response to OSCC-specific issues, two new deep learning models– MaskMeanShiftCNN and SV-OnionNet – have been developed. Pretraining results of Mask MeanShift CNN includes color, texture, and shape analysis for OSCC segmentation; and SV-OnionNet that particularly focuses on early-stage detection. The models attained ideal accuracy and low error rate of 98.94% and 1.05%, respectively, that suggest enhanced patients care [6]. Adding transfer learning to the image diagnostic model along with the texture- based properties such as CNN-SVM and all the feature fusion derivate methods; GLCM, HOG, LBP increased OSCC detection to 97% [7]. A similar strategy used Ef- ficientNetB3 to classify 1224 histopathological images of 230 patient samples with 99% accuracy, precision, and notable recall for potential OSCC early diagnosis [8]. Another study used transfer learning by AR, which DenseNet201 yielded the highest classification values than the RoI models, contrary to MobileNet, Inception V3 and Xception, thus supporting the usefulness of DL-CNN techniques for diagnosing this ailment [9]. Preprocessing based on median filter, feature extraction based on energy and entropy, and classification based on a Support Vector Machine (SVM), and a K Nearest Neighbor (KNN) algorithm were also used, and the performance of the SVM models was higher than that of the KNN models in oral cancer image classification [10]. Finally, researchers assessed how transfer learning with pre-trained DCNNs (VGG16, VGG19, ResNet50) and a baseline DCNN developed with ten convolutional layers improves OSCC diagnostic performance by fine-tuning these models for smaller datasets [11].

Table.1. Review paper analysis

Sl. No	Dataset	Algorithm	Accuracy
1	800 histopathological images UOP IMC dataset [5].	StabL using 5-fold Monte Carlo cross- validation strategy	93.43% and 96.66%
2	Oral Cancer Imaging Database (OCID) [6].	MaskMeanShiftCNN and SV-OnionNet	98.94%
3	The dataset comprise 5192 images ac- quired from biopsy slides at 100× zoom [7].	CNN and SVM	97.00%
4	This dataset contains a total of 1,224 images that are publicly accessible [8].	EfficientNetB3 architecture.	99%
5	The dataset is composed of 1000 oral picture images collected from Google and other verified sources [9].	DL-CNN model using DenseNet201	84.70%
6	The dataset comprises of 1224 histopathological images [10].	SVM, KNN	SVM accuracy 98% and KNN

			accuracy 83%
7	1035 harmless and 1154 harmful im- age from Mendeley datasets leading to a total of 2000 patches per category [11].	Model Deep Convolutional Neural Networks (DCNNs) with algorithm VGG16, VGG19, ResNet50, Incep- tionV3, and MobileNet .	96.6%

3. Methodology

3.1.Dataset description

The dataset opted for the research was NDB-UFES dataset [12] which contains histopathological images along with clinical and demographic data of the patient. All total there are 237 images in PNG format which is subdivided into 3 types, 91 as OSCC, 89 as leukoplakia with dysplasia and 57 as leukoplakia without dysplasia. A hematoxylin- eosin stain was used to prepare the slides with biopsy of patients. The dataset also contains demographic and clinical data including gender, age, tobacco consumption, alcohol consumption, biopsy, etc. stored in a CSV format. The CSV file contain all total 237 entries with 17 columns.

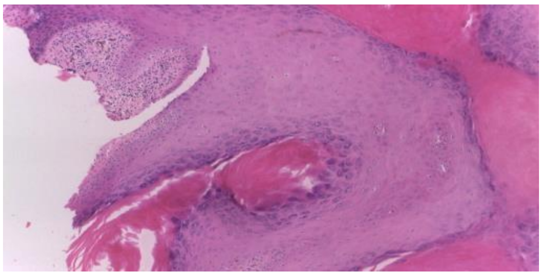

Fig.1. Sample images from dataset

Table.2. Data Dictionary

Name	Column name	Description
ID	public_id	A unique ID for each sample.
Filename	path	Histopathologic image filename.
Lesion localization	localization	Lesion's localization in body. (Tongue, Gingiva, Buccal mucosa, Floor of mouth, Lip, Palate).
Lesion larger size	larger_size	Larger size of the lesion in centimeters.
Diagnosis	diagnosis	Lesion diagnosis. (OSCC, Leukoplakia with dysplasia, Leukoplakia without dysplasia).
Dysplasia severity	dysplasia_severity	Severity of the dysplasia in the lesion. (Mild, Severe, Moderate)
Gender	gender	Patient's gender. Male or Female (M, F).
Age group	Age_group	Patient's age group. Group 0 for lesser than 40 years. Group 1 for ages between 41 and 60 years, included. Group 2 for ages greater than 60 years.
Skin color	Skin_color	Patient's skin color. (Black, Brown, White and Others).
Tobacco use	tobacco_use	Patient's tobacco use. (Yes, no, Former, Not Informed).
Alcohol consump- tion	Alcohol_con- sumption	Patient's alcohol consumption. (Yes, no, Former, Not Informed).
Sun Exposure	Sun_exposure	Patient's sun exposure in hours. It is -1, if not informed.

3.2 Model Formulation

This research was implemented using machine learning approach where different supervised learning algorithms were implemented such as SVM, decision tree, random forest, KNN, logistic regression and naïve byes to get a comparative analysis of the traditional algorithms. A multimodal approach was followed where both the image features and clinical data were combined and used for implementation. The image features were extracted with a pre-trained deep learning model ResNet50. It was further combined with clinical data and trained with various supervised learning algorithms. The multimodal approach was used to maximize the performance for better results.

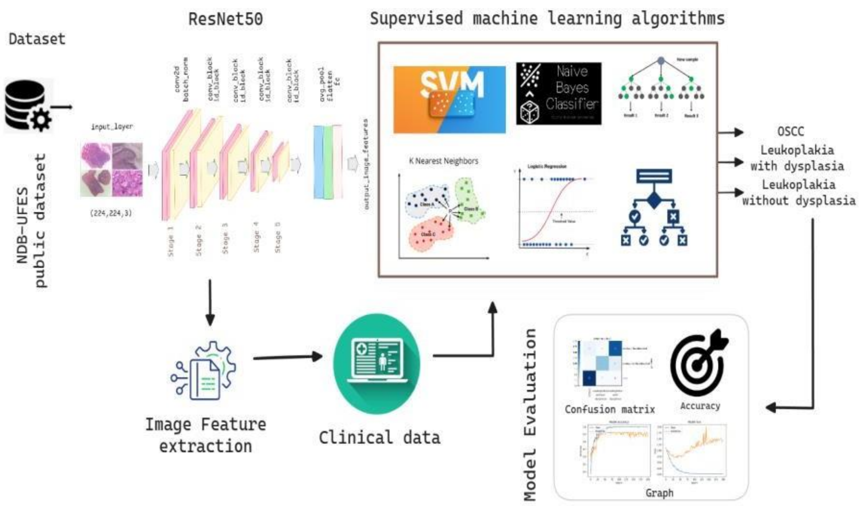

Fig.2. Model architecture

4. Results

All total 6 different supervised learning algorithms were implemented with ResNet50 as a pre-trained deep learning model for image feature extraction. At first the image features were extracted using ResNet50 and the obtained feature was combined with the clinical data of corresponding patients with the diagnosis column of CSV file as the connecting attribute. After the mapping of image feature with clinical data the combined data is passed through various supervised learning algorithms for training purposes and at the end the performance of each model was investigated with classification report including Recall, Precision, f1-score, Accuracy metric and confusion matrix. Since the NDB-UFES dataset was used which consisted of both image and clinical data so the acquired model was a multimodal. Out of 237 images 80% were used to train the model and 20% was used for testing purpose. This proposed work was done using Keras and TensorFlow libraries using Anaconda as the virtual environment, Spyder and Py- thon coding for implementation purposes.

To evaluate the performance of the proposed model, the confusion matrix was used to compute accuracy, precision, sensitivity and specificity using the equations below. True positive TP and true negative TN, false positive are the metric of confusion matrix rep- resenting correct predictions. Similarly, FP and false negative FN are the metric of con- fusion matrix representing incorrect predictions.

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \times 100\% \quad (1)$$
$$\text{Precision} = TP/(TP+FP) \times 100\% \quad (2)$$
$$\text{Sensitivity} = TP/(TP+FN) \times 100\% \quad (3)$$
$$\text{Specificity} = TN/(TN+TP) \times 100\% \quad (4)$$

4.1 SVM

Table.1. shown below provides the performance acquired by the SVM model. The SVM model was implemented with 4 different kernels, i.e. linear kernel, polynomial kernel, sigmoid kernel and RBF kernel.

4.1.1 Linear Kernel

With the implementation of linear kernel, a decision boundary is produced i.e., a hyper- plane which evenly separates the data points of all different classes in a linear manner, assuming the relationship to be linear. It computes a dot product of input vectors in original space without converting them into higher dimensional space. The training ac- curacy obtained for linear kernel was ~85% and test accuracy were ~81%.

Table.1. Classification report

	Precision	Recall	F1-score	Support
Leukoplakia with dysplasia	0.82	0.78	0.80	18
Leukoplakia without dysplasia	0.80	0.80	0.80	10
OSCC	0.81	0.85	0.83	20
Accuracy			0.81	48
Macro avg	0.81	0.81	0.81	48
Weighted avg	0.81	0.81	0.81	48

Fig.3. Below shows the confusion matrix were among 48 instances obtained for test set 18 were correctly classified as Leukoplakia with dysplasia class, 10 as Leukoplakia without dysplasia class and 20 as OSCC class. Referring to the figure below it can be easily understood how many instances were correctly classified by the SVM model while testing.

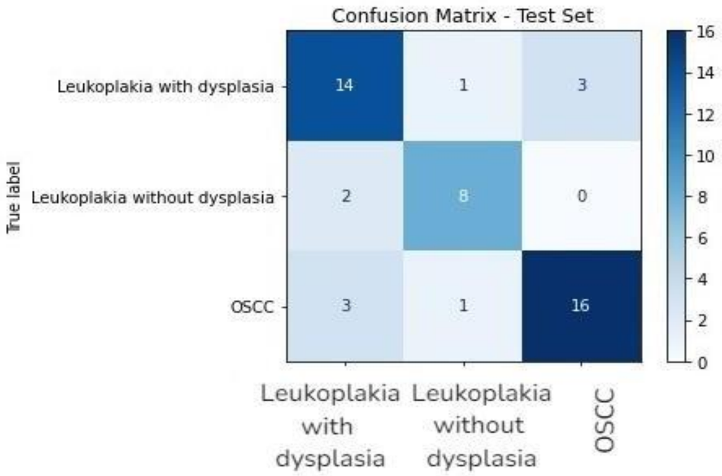

Fig.3. Confusion matrix

4.1.2 Polynomial kernel

Polynomial kernel uses the polynomial function and maps the data points from original space to a new higher dimensional space. It maps to higher dimensional by computing the dot product of the data points and solves the classification problem if the data is not linearly separable. The training accuracy obtained using polynomial kernel was ~57% and the test accuracy was ~58%. **Table.2.** Below provides the classification report including precision, recall, f1-score and support for better evaluation.

Table.2. Classification report

	Precision	Recall	F1-score	Support
Leukoplakia with dysplasia	0.58	0.61	0.59	18
Leukoplakia without dysplasia	0.00	0.00	0.00	10
OSCC	0.59	0.85	0.69	20
Accuracy			0.58	48
Macro avg	0.39	0.49	0.43	48
Weighted avg	0.46	0.58	0.51	48

Fig.4. Below shows the confusion matrix were among 48 instances obtained for test set 11 were correctly classified as Leukoplakia with dysplasia class, 0 as Leukoplakia with- out dysplasia class and 17 as OSCC class.

Referring to the figure below it can be easily understood how many instances were correctly classified by the SVM model while test- ing.

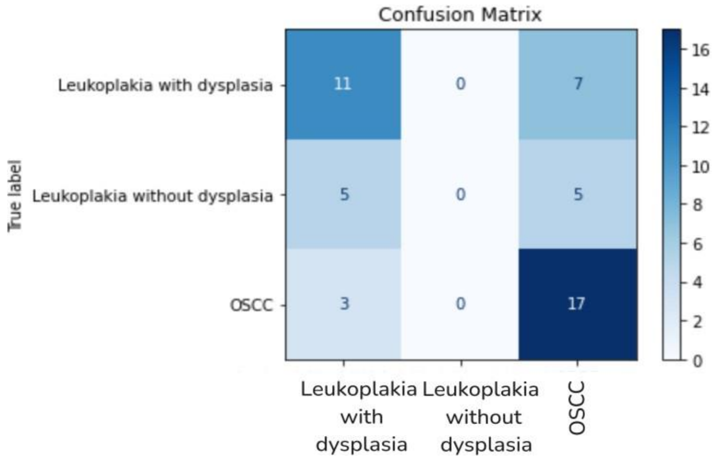

Fig.4. Confusion matrix

4.1.3 Sigmoid kernel

The sigmoid kernel is used to introduce sigmoidal and nonlinear relationships between the data points. The training accuracy obtained with sigmoid kernel was ~56% and the test accuracy was ~56%.

Table.3. Classification report

	Precision	Recall	F1-score	Support
Leukoplakia with dysplasia	0.62	0.56	0.59	18
Leukoplakia without dysplasia	0.00	0.00	0.00	10
OSCC	0.53	0.85	0.65	20
Accuracy			0.56	48
Macro avg	0.39	0.47	0.41	48
Weighted avg	0.46	0.56	0.49	48

Fig.5. Below shows the confusion matrix among 48 instances obtained for test set 10 were correctly classified as Leukoplakia with dysplasia class, 0 as Leukoplakia without dysplasia class and 17 as OSCC class. Referring to the figure below it can be easily understood how many instances were correctly classified by the SVM model while testing.

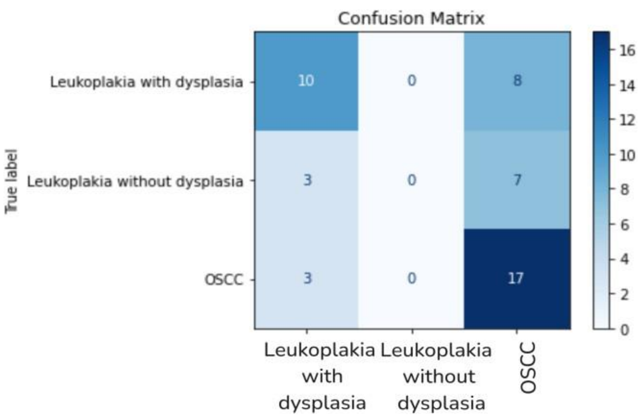

Fig.5. Confusion matrix

4.2.Decision Tree

Decision tree, which is one of the traditional approaches of supervised machine learning algorithm was used along with ResNet50 for implementation. The training accuracy obtained was 100% and test accuracy was ~71%.

Table.4. Classification report

	Precision	Recall	F1-score	Support
Leukoplakia with dysplasia	0.67	0.78	0.72	18
Leukoplakia without dysplasia	0.75	0.90	0.82	10
OSCC	0.73	0.55	0.63	20
Accuracy			0.71	48
Macro avg	0.72	0.74	0.72	48
Weighted avg	0.71	0.71	0.70	48

Fig.6. Below shows the confusion matrix among 48 instances obtained for test set 14 were correctly classified as Leukoplakia with dysplasia class, 9 as Leukoplakia without dysplasia class and 11 as OSCC class. Referring to the figure below it can be easily understood how many instances were correctly classified by the SVM model while testing.

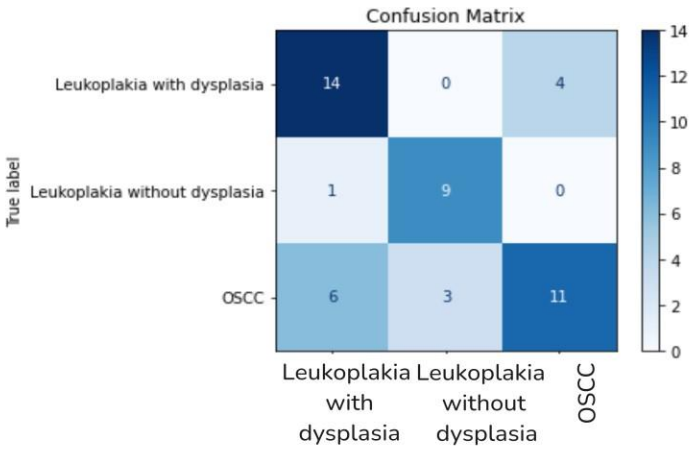

Fig.6. Confusion matrix

4.3.Random Forest

Random forest uses a collection of decision trees and performs the classification task. It usually works by combining outputs of multiple decision trees and concludes to a single result. Here the total number of trees used was 100 which results in training accuracy of 100% and test accuracy of ~62%. **Table.5.** Below provides the evaluation metric as a classification report.

Table.5. Classification report

	Precision	Recall	F1-score	Support
Leukoplakia with dysplasia	0.52	0.67	0.59	18
Leukoplakia without dysplasia	0.67	0.20	0.31	10
OSCC	0.73	0.80	0.76	20
Accuracy			0.62	48
Macro avg	0.64	0.56	0.55	48
Weighted avg	0.64	0.62	0.60	48

Fig.7. Below shows the confusion matrix were among 48 instances obtained for test set 12 were correctly classified as Leukoplakia with dysplasia class, 2 as Leukoplakia with- out dysplasia class and 16 as OSCC class. Referring to the figure below it can be easily understood how many instances were correctly classified by the SVM model while test- ing.

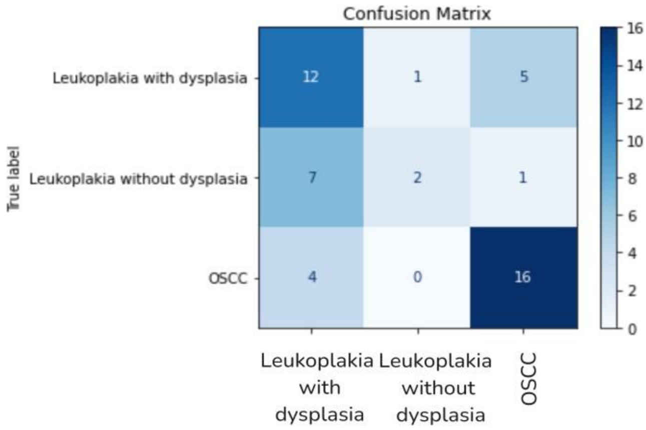

Fig.7. Confusion matrix

4.4.KNN

KNN, which is another supervised learning method is a simple and powerful at the same time, it is used for regression as well as classification task and it works based on the similarities among the data points hence it is also termed as lazy algorithm. Basically, for new input data it looks for K most similar points among the training data and assign the label which is likely the most common among all. The value of K used was 3 and training accuracy obtained was ~97% and test accuracy obtained was ~89%. **Ta- ble.6.** Below provides a classification report of the model for better evaluation.

Table.6. Classification report

	Precision	Recall	F1-score	Support
Leukoplakia with dysplasia	0.85	0.94	0.89	18
Leukoplakia without dysplasia	1.00	0.90	0.95	10
OSCC	0.89	0.85	0.87	20
Accuracy			0.90	48
Macro avg	0.91	0.90	0.90	48
Weighted avg	0.90	0.90	0.90	48

Fig.8. Below shows the confusion matrix among 48 instances obtained for test set 17 were correctly classified as Leukoplakia with dysplasia class, 9 as Leukoplakia without dysplasia class and 17 as OSCC class. Referring to the figure below it can be easily understood how many instances were correctly classified by the SVM model while testing.

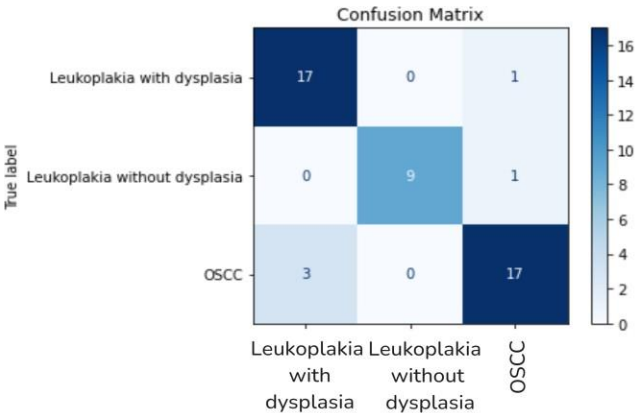

Fig.8. Confusion matrix

4.5.Logistic Regression

Logistic regression is one of the popular machine learning algorithms used for classification tasks. It works on the probability principle where the motive of the model is to find the probability that the provided input belongs to which class. It uses a sigmoid function which basically maps the values in the range of [0,1] so that it can be interpreted as probability. The training accuracy obtained for the model was ~84% and test accuracy was ~79%. **Table.7.** Below provides some evaluation metrics as a classification report.

Table.7. Classification report

	Precision	Recall	F1-score	Support
Leukoplakia with dysplasia	0.78	0.78	0.78	18
Leukoplakia without dysplasia	0.80	080	0.84	10
OSCC	0.80	0.80	0.80	20
Accuracy			0.79	48
Macro avg	0.79	0.79	0.79	48
Weighted avg	0.79	0.79	0.79	48

Fig.9. Below shows the confusion matrix among 48 instances obtained for test set 13 were correctly classified as Leukoplakia with dysplasia class, 8 as Leukoplakia without dysplasia class and 16 as OSCC class. Referring to the figure below it can be easily understood how many instances were correctly classified by the SVM model while testing.

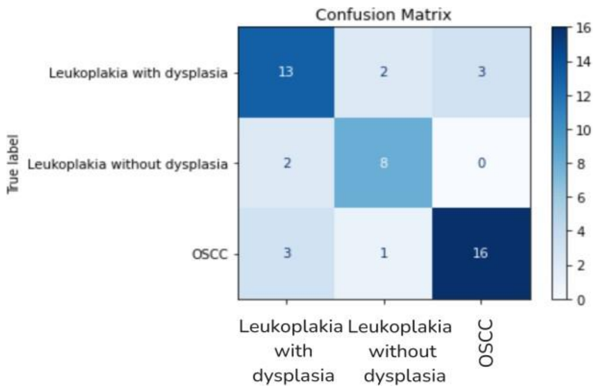

Fig.9. **Confusion matrix**

4.6.Naive Byes

Naive byes are amongst the supervised learning methods, simple to use and is based on the Bayes theorem. It helps in classification tasks by calculating probability that the input data points belong to each class and assign the input data to the class with higher probability. The main assumption in naïve byes is that all the features are independent. The training accuracy obtained for the model was ~60% and test accuracy obtained was ~57%. **Table.8.** Below is the classification report of the model.

Table.8. Classification report

	Precision	**Recall**	**F1-score**	**Support**
Leukoplakia with dysplasia	0.44	0.44	0.44	18
Leukoplakia without dysplasia	0.43	0.90	0.58	10
OSCC	0.89	0.40	0.55	20
Accuracy			0.52	48
Macro avg	0.59	0.58	0.53	48
Weighted avg	0.63	0.52	0.52	48

Fig.10. Below shows the confusion matrix were among 48 instances obtained for test 8 were correctly classified as Leukoplakia with dysplasia class, 9 as Leukoplakia with- out dysplasia class and 8 as OSCC class. Referring to the figure below it can be easily understood how many instances were correctly classified by the SVM model while test- ing.

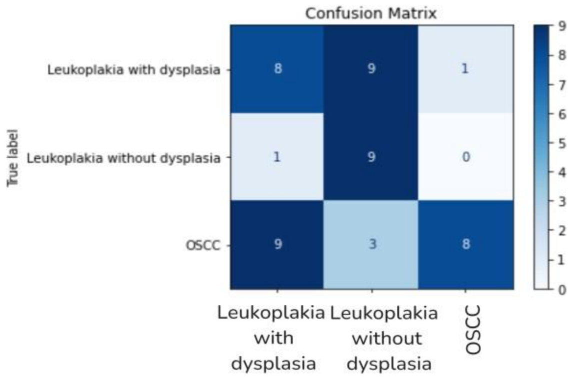

Fig.10. Confusion matrix

5. Comparative analysis of models

Table.9. Below is a brief comparative analysis of all the models performed for this research. From the table it is concluded that KNN performs best in both training (97%) and test data (89%) indicating that the model acquired an effective generalization capacity. On the other hand, support vector machine SVM with linear kernel performs best among all kernels with the training accuracy of 85% and test accuracy of 81% suggesting that it was a good fit for the data among other kernels. Logistic regression shows a moderate performance with training accuracy of 84% and test accuracy of 79%. Decision tree and random forest shows perfection in training (100%) but due to over- fitting results in low test accuracy of 71% and 62% respectively. Among all supervised methods performed naïve byes and SVM with sigmoid and polynomial kernel shows very poor performance indication it was not suitable for the dataset. Hence, KNN and linear SVM seem to be the most balanced model for the dataset.

Table.9. Comparative analysis of models

SL. No.	**Algorithm**	**Training Accuracy**	**Test Accuracy**
1.	SVM (linear kernel)	85%	81%
2.	SVM (polynomial kernel)	57%	58%
3.	SVM (sigmoid kernel)	56%	56%
4.	Decision Tree	100%	71%
5.	Random Forest	100%	62%

6.	KNN	97%	89%
7.	Logistic Regression	84%	79%
8.	Naive Byes	60%	52%

6. Conclusion

The research proposes a new method for the early detection of OSCC with the help of histopathological images, which is very promising for assisting clinicians by making diagnoses highly accurate while reducing workload and enhancing cost-effectiveness. The dataset contains 237 histopathological images with clinical-demographic data di- vided into OSCC, leukoplakia with dysplasia, and leukoplakia without dysplasia. This investigation followed a multimodal approach: It fused image features extracted using pre-trained ResNet50 with clinical data and evaluated different supervised learning algorithms, namely SVM-Linear, Polynomial, Sigmoid, and RBF kernels, Decision Tree, Random Forest, K-Nearest Neighbors, Logistic Regression, and Naive Bayes. Among these models, the most efficient was KNN with 89% accuracy, which also showed very good generalization capability. Next best was the linear SVM, which showed 81% accuracy and is comparatively simpler yet reliable. Logistic Regression performed quite balanced. While Decision Tree and Random Forest suffered from overfitting, they had high training accuracy but poor test performance. Poor performers included Naive Bayes and SVM with polynomial and sigmoid kernels, proving to be a bad fit on this dataset.

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