Revolutionizing Image Classification with MopileNetV3, PCA, and Bayesian-Optimized Algorithms

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Abstract.
The field of image classification has made great strides with Machine Learning (ML) and Deep Learning (DL), but still encounters difficulties in attaining high efficiency and accuracy. MobileNetV3 architecture, which is famous for its performance and dept, holds a chance for betterment when utilized together with advanced algorithms. Though MobileNetV3 has been successful, there exists an opportunity to use techniques of dimensionality reduction as well as optimization to improve its performance. To this point, studies have mainly concentrated on using MobileNetV3 for image classification. However, these methods mentioned above have not been thoroughly examined in combination. This research seeks to create a new image classification model through integrating MobileNetV3 with Principal Component Analysis (PCA) and Bayesian-optimized algorithms. The aims are diminishing computational complexity, enhancing classification accuracy and optimizing model parameters. The study concentrates on image classification tasks with publicly accessible datasets. It investigates the integration regarding DL together with statistic as well as optimization methods to handle the existing limitations. The research uses a two-step method. First, it employs MobileNetV3 for extracting features and after that reduces its dimensions using PCA. Secondly, the research applies Bayesian Optimization (BO) for fine-tuning model parameters. The suggested approaches are assessed with the use of standard metrics and in comparison, with baseline models.
The integration regarding MobileNetV3 with BO and PCA showed an important advance in classification accuracy. The model which has been optimized through Bayesian method performed better than the baseline MobileNetV3; it achieved a classification accuracy of 96.17%, whereas the model without any optimization reached only 66.57% accuracy rate. Moreover, for the optimized model but not using (BO), we got recall 66.59%, precision 66.39%, and F1 score 65.60%. For the same one, but now with (BO), we saw results like this: precision at 98.88%, recall 98.48%, and F1score is 98.67% - both these measures improved significantly. The computational cost was brought down by using dimensionality reduction with PCA. The research brings an important contribution to image classification area because it suggests a robust model that merges DL with advanced statistical as well as optimization methods. The outcomes emphasize how much promise this combined technique holds for improving tasks related to classifying images.
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Keywords: Deep Learning, Machine learning, Principal Component Analysis (PCA), MobileNetV3, eXtreme Gradient Boosting (XGBOOST).

1. Introduction

The teeth and mouth are an integral part of the body, supporting and enabling essential human functions, and the mouth is a fundamental feature of personal identity. Oral health is subjective and dynamic, enabling eating, speaking, smiling, and socializing, without discomfort, pain, or embarrassment. Good oral health reflects an individual's ability to adapt to physiological changes throughout life and to maintain their own teeth and mouth through independent self-care **[1]**. Oral diseases and disorders, although largely preventable, are ubiquitous and affect the vast majority of the world's population with varying degrees of severity. The available mechanisms of oral disease prevention are effective at the individual level and have also had success at the population level. However, although the severity of oral diseases has been reduced, they are still highly prevalent and there is scope for development of new approaches to prevention that are less reliant on behavioral change at the individual level **[2]**. Oral disease is a pathological phenomenon that occurs in the oral cavity under the conditions of damage by external physical and chemical factors, invasion by pathogens, and systemic diseases, characterized by high incidence **[3]**.

Artificial intelligence (AI) is being utilized to produce intelligent robots which could do various tasks that would normally require human brains. Artificial intelligence is vital to the development of new technologies. AI is a general phrase for all the various technologies required to give machines intelligence comparable to that of humans. Machine learning (ML) is an algorithm-based self-learning system that falls under the umbrella of artificial intelligence (AI). A subset of ML called Deep Learning (DL) is typically applied to large databases **[4]**. account everything mentioned above, dental diseases place a financial strain on society because they affect treatment costs directly, indirectly, and intangibly through lost productivity, speaking, eating, and smiling difficulties, as well as behaviors which could interfere with family and social activities **[5]**.

Previous studies have addressed identify teeth in dental periapical films **[6]**, teeth recognition model **[7]**, dental restorations in the panoramic radiographs **[8]**, automatic periodontal disease detection in the orthodontic patients **[9]**, staging periodontitis on the dental panoramic radiographs **[10]**, recognize inflamed disease sites in intraoral photos **[11]**, identify white spot lesions in dental photos **[12]**, the dental periapical radiographs **[13]**, to categorize teeth as caries- or non-caries, dental visual images and deep neural network (CNN) have been utilized **[14]**, identification and categorization of the common dental problems in panoramic X-ray images **[15] [16]**, six dental diseases are recognizing tooth periapical disease, wear, periodontitis, tooth decay, missing teeth, and impacted teeth **[17]**, Investigated using DL object detection models in place of X-rays for detecting dental cavities **[18]**, DL-based oral disease diagnosis. Using InceptionResNet-V2 **[19]**, classifying teeth with periodontal diseases using frontal optical color images **[20]**, and training a CNN-based model for automatic classification of oral lesion images **[21]**.The deep feed forward ANN, which is widely utilized for visual image processing, is adapted into CNN. The network can encrypt image properties thanks to its convolution layer and pooling layer**[22]** With the use of the ML method known as transfer learning (TL), a pre-trained model that is built on a large data-set is utilized as a starting point for tackling a

new assignment. Instead of starting from scratch and training a new model on a limited dataset, TL entails optimizing a pre-trained model through utilizing previously learnt features and tailoring them to the current task. In DL, where training large models on vast data-sets could be expensive and time-consuming, TL is especially useful**[23]**. Convolutional neural network architectures have been proposed recently to tackle many convolutional different problems and improve their performance in terms of speed and size. Efficient neural networks implementing the depth wise convolution structure such as Mobile Nets **[24]** The architecture of MobileNetV3 is composed of a series of bottleneck blocks. Some of the bottleneck blocks include residual structure **[25]**. Is a recently released machine learning algorithm that has shown exceptional capability for modeling complex systems and is the most superior machine learning algorithm in terms of prediction accuracy and interpretability and classification versatility. XGBoost is an enhanced distributed scaling enhancement library that is built to be extremely powerful, adaptable, and portable. It uses augmented scaling to incorporate machine learning algorithms. It is a parallel tree boost that addresses a variety of data science problems quickly and accurately .The gradient boosting algorithm known as XGBOOST (Extreme Gradient Boosting) was enhanced in terms of flexibility, scalability, and efficiency**[26]**. In our research, we will propose a new model using two methods: the first method is to reduce dimensionality with PCA method depending on transfer learning (MopileNetV3), after that we enhance best decision through applying ensemble decision making (XGBOOST) when creating the model. Secondly, we can apply the BO on ensemble methods. This approach helps us optimize and select the best decision to create our optimize model.
Moreover, we use transfer learning to extract features by MopileNetV3 then dimensionality reduce by PCA technique. According to these methods we will classify diseases of the mouth and oral, including: Canker sores (CaS), Gangivostomatitis (Gum), Oral lichen planus (OLP), Cold sores (CoS), Mouth cancer (MC), Oral thrush (OT) and Oral cancer (OC). In addition, we will enhance and improve the Accuracy and Consistency, Frequency of Diagnosis, Patient Comfort, Scalability and Data Handling.

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2. Methods

The research methodology can be defined as a systematic approach utilized for the purpose of conducting research as well as gathering relevant data for answering research questions or investigating a specific problem. It outlines the procedures, methods, along with the tools that researchers apply for analyzing, designing, executing, and planning their studies. A well-defined research methodology is important to ensure the reliability, validity, and credibility regarding the research findings **[27]**.The method includes four steps; the first step is related work this include: the Oral and Mouth Disease Diagnosis (OMDD) taxonomy to Study the limitation in these researches and explain the gap of the MODD study as definition in the introduction. The second one is Dataset collection that includes: find the dataset from google dataset engine, dataset description that include 7 disease based on 5128 images, and selecting environment using Anaconda. Third step is Preparation dataset include: data augmentation, label encoding, feature extraction, and dimensionality reduction. Fourth step is evaluation of optimum model, it include: initiation parameters of XGBOOST according to using Ensemble learning (Boosting), proposed model (with and without Bayesian optimization (BO)) figure (1), and in finally evaluation the model by the confusion matrix.

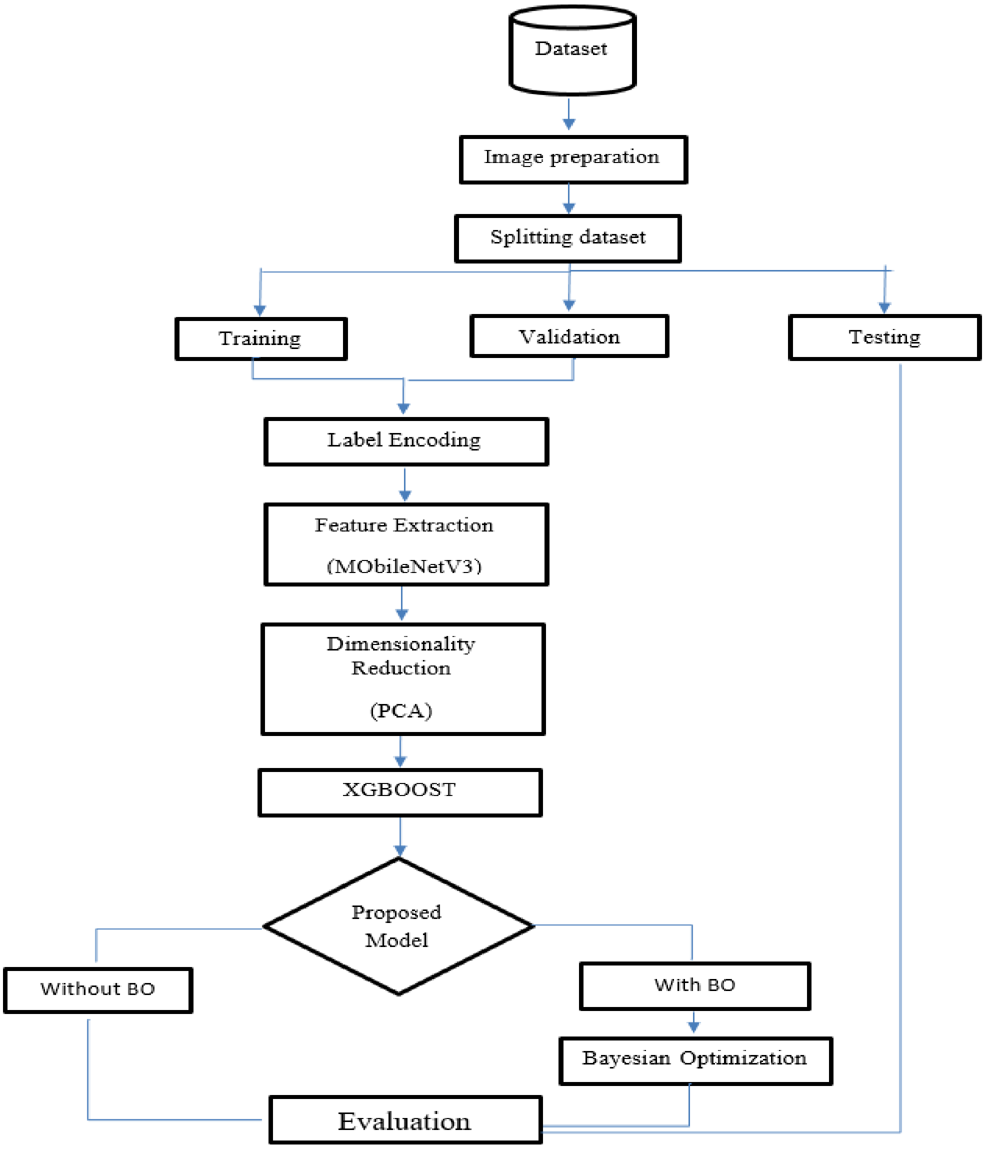

Figure 1: Research methodology step

2.1. Dataset Description

The "Mouth and Oral Disease (MOD) dataset," which is publicly available, was made available by "dental clinics in Okara, Punjab, Pakistan, and other locations (dental websites, etc.)" Table 1: MODD dataset description lists the 5128 samples which comprise the raw Mouth and Oral Disease Diagnosis

(MODD) data-set. The total number of labels and samples for each category is also included in the table. The class labels in this collection reflect seven illnesses of the mouth and oral cavity: canker sores, cold sores, Gangivostomatitis, mouth cancer, oral thrush, oral cancer, and oral lichen planus. No one had disclosed their gender, height, or age during, prior to, or following the photo shoot. The MODD dataset was labeled with the assistance of skilled pretensioners. Figure (2) is show one of image to each class in dataset.

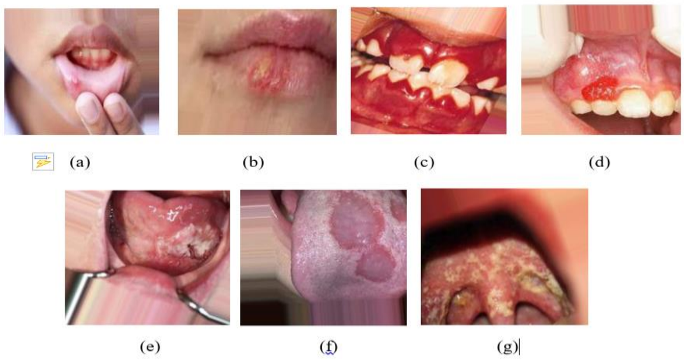

Figure 2:(a) CaS, (b) CoS, (c) Gum, (d) MC, (e) OC, (f) OLP and (g) OT MODD data-set classes

Table 1: MODD dataset description

Class labels	**Images**
Canker Sores (CaS)	729
Gangivostomatitis (Gum)	749
Cold Sores (CoS)	733
Oral Cancer (OC)	740
Mouth Cancer (MC)	720
Oral Thrush (OT)	723
Oral lichen planus (OLP)	734
Total Samples (TS)	5128

In this paper, the data set divided into three sections: training, testing and validation, each stage of which is divided into seven sections for seven diseases of the mouth and gums, which are of the multi-class type. It is a balanced data set, each of which has dimensions of 224*224 pixels. Table 2: MODD dataset (Training, Testing, and Validation) provides a description of aforementioned dataset

Table 2: MODD dataset (Training, Testing, and Validation)

Dataset	No. of samples	**No. of MODD image**

		Training	Testing	Validation
MODD dataset	5128	3091	1017	1020

2.2. Exploratory Data Analysis and Visualize

To identify the relevant information, we will create some statistics and visualize this data. The data sets were subjected to a range of exploratory data analysis techniques, and the resulting data sets were displayed to offer an effective understanding of MODD. Visualization facilitates comprehension of MODD instances. From the representation EDA, it has been shown that the dataset is divided into three parts: (60%) for training with 441 image in CaS, 445 image in CoS, 455 image in Gum, 432 image in MC, 452 image in OC, 434 in OLP and 432 image in OT and (20%) for the both testing and validation with 144 image in each of CaS, CoS, MC, and OC, 147 image in Gum, 150 image in OLP for each testing and validation and 144 image in OT for testing, 147 image in OT for validation

In this result, the number of images for each disease from each stage and the class distribution chart appear as shown in figure (3). However, due to space constraints, displaying them is not possible at this time.

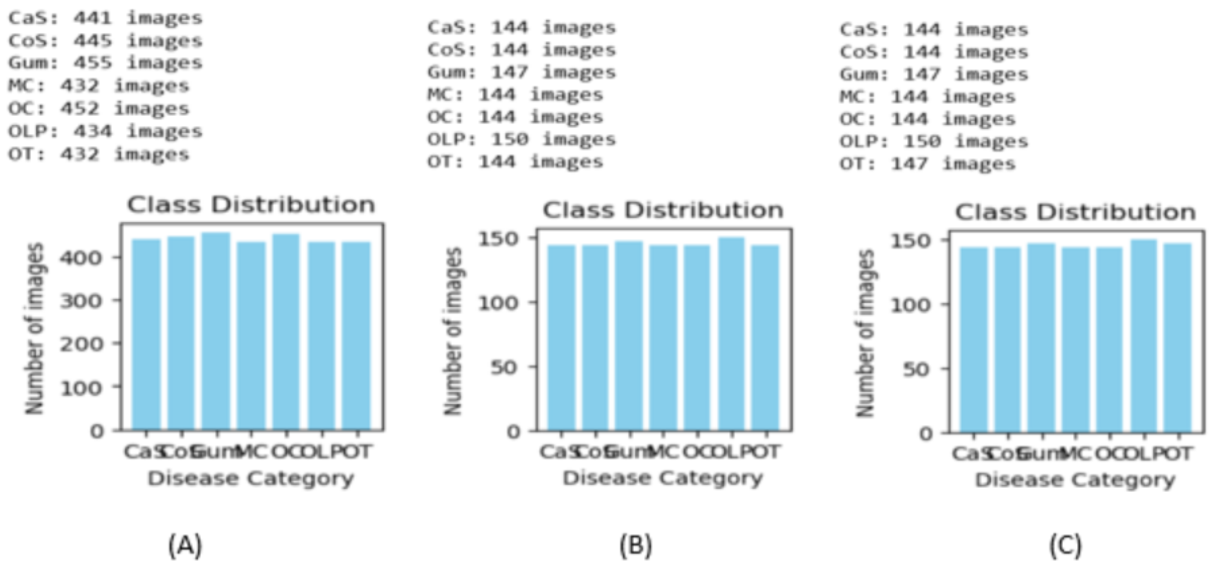

Figure 3: The result of EDA for (A) training, (B) testing, and(C) validation

2.3. Statistics for Testing, Training, and Validation Dataset

These statistics help in understanding the distribution of brightness levels, which is important for preprocessing and normalization tasks. The histogram also makes clear how often different values occur, giving a better idea about the distribution of data sets. Figure (4) and Figure (5) are showing what we got from Statistics for (A) Training (B) Testing and (C) Validation Datasets.

A

Statistics for Training Data:
Mean Brightness: 133.5062915838094
Median Brightness: 131.6057676977041
Mode Brightness: 137.87350526147958

B

Statistics for Testing Data:
Mean Brightness: 133.73237043365467
Median Brightness: 131.32495615433675
Mode Brightness: 79.52861926020408

C

Statistics for Validation Data:
Mean Brightness: 133.27110676301768
Median Brightness: 136.48084741709184
Mode Brightness: 126.61152742346938

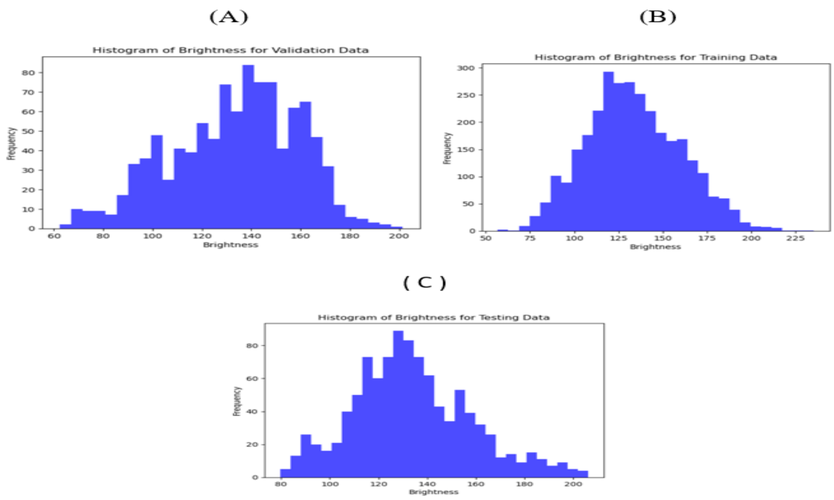

Figure 4: (A) Statistics for Training Data, (B) Statistics for Testing Data (C) Statistics for Validation Data

Figure 5: Result for Histogram of Brightness for (A) training, (b) testing, and (C) validation Data

2.4 Training, Testing, and Validation Features Sample (CaS)

These features are crucial for maximizing the model's performance and adjusting its parameters within the validation set. They also form a basis to gauge how well it does initially during training and tweak any adjustable settings accordingly. Hence, the feature samples from "Training Features Sample", "Testing Features Sample" and "Validation Features Sample" clarify diverse characteristics used in every dataset – this helps understand data attributes across model's stages of training, testing as well validating. The disease CaS was taken for example as can be seen in table 3**:** the Result of Training, Testing, and Validation Features Sample for the disease CaS.

Table 3: The Result of Training, Testing, and Validation Features Sample for the disease CaS

Feature sample	No.	Brightness	Contrast	Saturation	Sharpness	Hue	Category
Training	0	192.167809	33.964650	122.397082	-0.168058	6.136001	CaS
	1	121.260902	33.042695	116.819356	-0.035316	6.845006	CaS
	2	137.877372	36.617221	110.052475	-0.157545	6.220484	CaS
	3	126.517419	31.907667	120.652244	-0.004524	5.919523	CaS
	4	133.027942	36.865754	104.708546	-0.238909	7.319595	CaS

Testing	0	206.221281	44.130182	47.989417	0.013403	88.878129	CaS
	1	200.767478	43.060150	53.977519	0.031140	80.088050	CaS
	2	194.795061	44.738309	59.355210	-0.066755	87.174964	CaS
	3	191.951889	45.691815	61.525949	-0.041912	86.807478	CaS
	4	194.320580	44.574301	63.170898	-0.005680	78.091279	CaS
Validation	0	137.017000	38.721601	144.196688	0.046576	14.822445	CaS
	1	135.622070	27.245461	148.394651	0.042869	15.743343	CaS
	2	132.882912	27.141358	150.421895	-0.068170	14.209283	CaS
	3	133.162887	23.684673	149.537229	-0.036900	14.352021	CaS
	4	131.256059	47.155815	145.045540	0.093650	15.545759	CaS

3.Result and Discussion

After completing the preparation and processing of the images, as well as dividing the dataset, it is now ready for using. Model training was conducted prior to feature extraction due to the nature of the model's properties, with the trainer handling this task. A detailed discussion of the results from each step of preparing the model will follow:

3.1 Label Encoding

In ML, label encoding is a technique used to transform categorical data into numerical data. Since many ML algorithms could just process numerical input, this transformation is crucial. Each separate category in a feature is given a unique integer via the label encoding procedure.

3.2 Dimensionality Reduce Using PCA

Any high-dimensional data analysis could use the preprocessing procedure known as DR before the data is modeled and shown. DR could be performed in two ways. Essential features are chosen from the input data set using feature selection techniques in the first approach. Feature extractions, the second technique, generate new features from the already features in the input dataset. Combining or separating the feature extraction and selection processes enhances the DL model's computed accuracy and precision **[28]**. Principal Component Analysis (PCA) can be defined as a method utilized for dimensionality reduction while preserving as much variance as possible in the dataset.

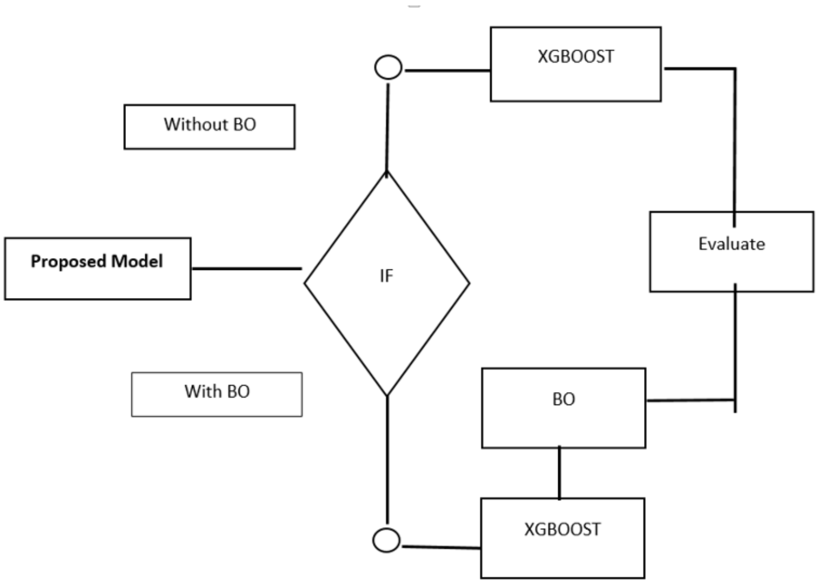

Figure 6: Flowchart of Proposed Model

3.3 MobileNetV3 and XGBOOST without Bayesian Optimization (BO)

Because of its sample efficiency, BO is a widely used paradigm for improving the hyperparameters of ML models [28]. After the features have been extracted, the dimensions have been reduced, and each stage has been reviewed, the space function will be loaded to prepare the model that was trained for the following operations**.** Figure (6) Flowchart of Proposed Model.

Table 3: Confusion Matrix of MobileNetV3 and XGBOOST

		Predicted							
		CaS	CoS	Gum	MC	OC	OLP	OT	Total
Actual	CaS	108	16	1	0	1	10	8	144
	CoS	4	140	0	0	0	0	0	144
	Gum	1	1	136	9	0	0	0	147
	MC	13	0	38	68	8	15	2	144
	OC	11	10	1	6	88	6	22	144
	OLP	5	2	4	10	9	74	46	150
	OT	21	22	2	5	3	28	63	144
Total		163	191	182	98	109	133	141	1017

To calculate the four criteria mathematically:

a) Accuracy:

Accuracy is determined by dividing the total number of predictions by the sum of correct predictions (diagonal elements).

$$accuracy = \frac{\text{sum of diagonal elements (correct predictions)}}{\text{Total number of predictions}}$$

Accuracy=108+140+136+68+88+74+63\108+16+1+1+10+8+4+140+1+1+136+9+13 +38+68+8+15+2+11+10+1+6+88+6+22+5+2+4+10+9+74+46+21+22+2+5+3+28+63

=677\1017≈ 0.6657.

b) Precision:

Precision measures the accuracy of positive predictions for a specific class. Mathematically, for each class i, precision is calculated as:

$$precision_i = \frac{\text{True Positive}_i}{\text{True Positive}_i + \text{false Positive}_i}$$

Precision for each class:

Class1: True Positive1=108, False Positive1=16+1+0+1+10+8=36

$$\frac{108}{108+36} \equiv 0.750$$

Class 2: True Positive2=140, False Positive2=4+1+0+10+2+22=39

$$\frac{140}{140+39} \equiv 0.782$$

Class 3: True Positive3=136, False Positive3=1+0+38+1+4+2=46

$$\frac{136}{136+46} \equiv 0.748$$

Class 4: True Positive4=68, False Positive4=13+38+8+15+5+3=82

$$\frac{68}{68+82} \equiv 0.453$$

Class 5: True Positive5=88, False Positive5=11+10+1+6+6+22=56

$$\frac{88}{88+56} \equiv 0.611$$

Class 6: True Positive6=74, False Positive6=5+2+4+10+9+46=76

$$\frac{74}{74+76} \equiv 0.493$$

Class 7: True Positive7=63, False Positive7=21+22+2+5+3+28=81

$$\frac{63}{63+81} \equiv 0.438$$

$$precision = \frac{\Sigma precision_i}{n} = 0.6639$$

Recall:

Recall for each class i

is determined by dividing the total number of actual instances of that class by the ratio of true positive predictions for that class.

$$Recall_{\,i} = \frac{\text{True Positive}_i}{\text{True Positive}_i + false\ Negative_{\,i}}$$

Recall for each class:

Class1: False Negative1=4+1+13+11+5+21=55→ $\frac{108}{108+55} \equiv 0.663$

Class 2: False Negative2= 16+1+0+10=27→ $\frac{140}{140+27} \equiv 0.839$

Class 3: False Negative3= 1+9=10→ $\frac{136}{136+10} \equiv 0.932$

Class 4: False Negative4= 13+38+8+15+5=79→ $\frac{68}{68+79} \equiv 0.462$

Class 5: False Negative5= 11+10+1+6+6=34→ $\frac{88}{88+34} \equiv 0.721$

Class 6: False Negative6= 5+2+4+10+9+46=76→ $\frac{74}{74+76} \equiv 0.493$

Class 7: False Negative7= 21+22+2+5+3+28=81→ $\frac{63}{63+81} \equiv 0.438$

$$Recall = \frac{\Sigma Recall_i}{n} = 0.6659$$

c) F1 Score:

F1 Score for each class i is the harmonic mean of precision and recall for that class.

$$F1\ Score_i = 2 \times \frac{precision_{\,i} \times Recall_i}{precision_{\,i} + Recall_i}$$

F1 Score for each class:

Class1: $F1$=2× 0.750×0.663\0.750+0.663≈0.704

Class2: $F1$=2× 0.782×0.839\ 0.782+0.839≈0.810

Class3: $F1$=2× 0.748×0.932\ 0.748+0.932≈0.831

Class4: $F1$=2× 0.453×0.462\ 0.453+0.462≈0.457

Class5: $F1$=2× 0.611×0.721\ 0.611+0.721=0.661

Class6: $F1$=2× 0.493×0.493\ 0.493+0.493≈0.493

Class7: $F1=2\times 0.438\times0.438\backslash\ 0.438+0.438=0.438$

$$F1\ score = \frac{\Sigma F1\ score_i}{n}=0.656$$

3.4 MobileNetV3 and XGBOOST with Bayesian Optimization (BO)

Table 4: Confusion Matrix of MobileNetV3 and XGBOOST with BO

		Predicted							
		CaS	CoS	Gum	MC	OC	OLP	OT	Total
Actual	CaS	137	0	0	0	1	4	2	144
	CoS	0	144	0	0	0	0	0	144
	Gum	0	0	147	0	0	0	0	147
	MC	0	0	0	139	3	2	0	144
	OC	2	0	1	1	136	1	3	144
	OLP	5	0	1	5	1	137	1	150
	OT	4	0	0	1	1	0	138	144
Total		148	144	149	146	142	144	144	1017

True Positive (TP): Sum of values on the main diagonal (correctly predicted instances).

TP = 137 + 144 + 147 + 139 + 136 + 137 + 138 = 978

False Positives (FP): Sum of values in each column on the diagonal excluding true positives.

- Column sums: 2,0,1,0,1,0,1
- FP for each column (excluding diagonal value):

$$\text{FP} = (2 + 5 + 4) = 11$$

False Negatives (FN): Sum of values in each row on the diagonal excluding true positives.

- Row sums: 1,0,0,2,0,3,0
- FN for each row (excluding diagonal value):

$$\text{FN} = (1 + 0 + 0 + 5 + 1 + 5 + 1) = 13$$

TN=n-TP-FP-FN →TN=1017-978-11-13=15

a. Accuracy:

$$accuracy = \frac{\text{TP + TN}}{\text{Total number of Population}}$$

$$= \frac{978+15}{1017} \approx 0.9617$$

b. Precision:

$$Precision = \frac{TP}{TP + FP}$$

$$= \frac{978}{978+11} \approx 0.9888$$

c. Recall:

$$Recall = \frac{TP}{TP + FN}$$

$$= \frac{978}{978+13} \approx 0.9848$$

d. F1 score:

$$F1\ score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

$$= 2\times \frac{0.9888\times 0.9848}{0.9888+0.9848} \approx 0.9867$$

3.5 Comparison between MobileVetV3 without Optimization and with Optimization

The comparison is quite clear from the results and accuracy rates that have been proven, when the MobileNetV3 model was used and we using feature engineering to prepared the data architecture according to our objectives. We proposed a novel model by using advance methodology from a prepared dataset, scaling (ranged from 0 to 1), rotation (40^{0}), zooming (0.20), horizontal flipping (true), shear (20^{0}), label encoding, extracted features using MobileNetV3 then dimensionality reduce using PCA, proposed model using XGBOOST without BO where the result approximate 66.57% as a first method. While the proposed model using XGBOOST with BO the results was 96.17% as a second method table (5) and table (6). Moreover, comparison was made between trained models with receiver operating characteristic curve which shows the difference between the two models. Look at figure (7), which represents the curve of the first method, and the figure (8), which represents the curve of the second method.

Table 5: The accuracy of two method

dataset	Accuracy of XGBOOST With BO	Accuracy of XGBOOST Without BO
MODD dataset	96.17%	66.57%

Table 6: Recall, Precision and F1 score for two methods

Precision, Recall, and F1 score for two methods			
Model	Precision	Recall	F1 score
XGBOOST with BO	98.88%	98.48%	98.67&

XGBOOST without BO	66.39%	66.59%	65.60%

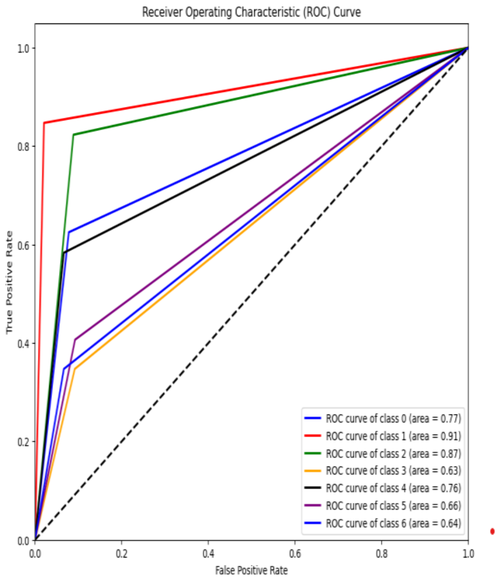

Figure 7: ROC Curve of first approach

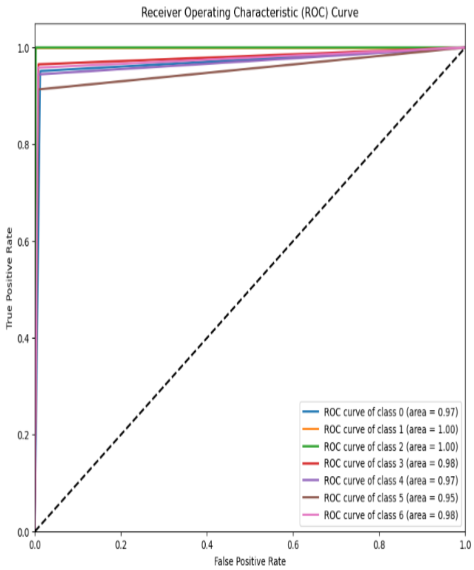

Figure 8: ROC Curve of second approach

4.Conclusion and Future Work

Diagnosing oral diseases was tackled using deep learning methods, comparing CNNs with XGBOOST, both with and without Bayesian optimization. Our study, conducted on the MODD dataset, revealed significant performance differences among the methods tested. Combining MobileNetV3 feature extraction with XGBOOST yielded 66.57% accuracy, while adding Bayesian optimization a

chieved nearly perfect precision at 96.17%. These results underscore the importance of hyper parameter tuning for model performance.

Implications extend to medical image analysis, suggesting that well-configured deep learning models could enhance oral disease diagnoses, potentially improving clinical decisions and patient outcomes. However, limitations include reliance on a single dataset and specific model designs, affecting generalizability and scalability. Future research should explore larger datasets, diverse model architectures, and incorporation of additional data modalities for comprehensive understanding and improved adaptability. Overall, our study lays the groundwork for leveraging advanced ML techniques in healthcare diagnostics and decision support systems

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المستخلص

حقق مجال تصنيف الصور خطوات كبيرة من خلال التعلم الآلي (ML) والتعلم العميق (DL)، ولكنه لا يزال يواجه صعوبات في تحقيق الكفاءة والدقة العالية. تتمتع بنية MobileNetV3، المشهورة بأدائها وعمقها، بفرصة للتحسين عند استخدامها مع الخوارزميات المتقدمة. على الرغم من نجاح MobileNetV3، إلا أن هناك فرصة لاستخدام تقنيات تقليل الأبعاد بالإضافة إلى التحسين لتحسين أدائها. إلى هذه النقطة، ركزت الدراسات بشكل أساسي على استخدام MobileNetV3 لتصنيف الصور. ومع ذلك، لم يتم فحص هذه الأساليب المذكورة أعلاه بدقة في تركيبة. يسعى هذا البحث إلى إنشاء نموذج جديد لتصنيف الصور من خلال دمج MobileNetV3 مع تحليل المكونات الرئيسية (PCA) وخوارزميات بايزي المحسنة. وتتمثل الأهداف في تقليل التعقيد الحسابي، وتعزيز دقة التصنيف، وتحسين معلمات النموذج. تركز الدراسة على مهام تصنيف الصور باستخدام مجموعات البيانات المتاحة للجمهور. إنه يبحث في التكامل فيما يتعلق بالتعلم مع DL مع الأساليب الإحصائية وكذلك طرق التحسين للتعامل مع القيود الحالية. يستخدم البحث طريقة من خطوتين. أولاً، يستخدم MobileNetV3 لاستخراج الميزات وبعد ذلك يقلل أبعاده باستخدام PCA. ثانيًا، يطبق البحث التحسين الافتراضي (BO) لضبط معلمات النموذج. يتم تقييم الأساليب المقترحة باستخدام المقاييس القياسية وبالمقارنة مع النماذج الأساسية.

أظهر التكامل فيما يتعلق بـ MobileNetV3 مع BO وPCA تقدمًا مهمًا في دقة التصنيف. النموذج الذي تم تحسينه من خلال الطريقة الافتراضية كان أداؤه أفضل من النموذج الأساسي MobileNetV3؛ فقد حقق دقة تصنيف بلغت 96.17%، في حين وصل النموذج دون أي تحسين إلى معدل دقة 66.57% فقط. علاوة على ذلك، بالنسبة للنموذج الأمثل ولكن بدون استخدام (BO)، حصلنا على نسبة استدعاء 66.59%، ودقة 66.39%، ودرجة 65.60% F1. لنفس الإجراء، ولكن الآن مع (BO)، رأينا نتائج مثل هذه: الدقة بنسبة 98.88%، والتذكر 98.48%، و98.67% F1score - تحسن كلا هذين المقياسين بشكل ملحوظ. تم تخفيض التكلفة الحسابية باستخدام تقليل الأبعاد باستخدام PCA. يقدم البحث مساهمة مهمة في مجال تصنيف الصور لأنه يقترح نموذجًا قويًا يدمج DL مع الأساليب الإحصائية وكذلك أساليب التحسين المتقدمة. تؤكد النتائج على مدى الوعد الذي تحمله هذه التقنية المدمجة لتحسين المهام المتعلقة بتصنيف الصور.