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Enhancing Age Determination From Panoramic Dental Radiographs Through Machine Learning

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Abstract

In anthropological research, forensic odontology, and clinical dentistry, it is essential to accurately determine the age from dental radiographs. In order to identify age from panoramic dental X-rays, this study suggests a hybrid machine learning method that combines the Synthetic Minority Over-sampling Technique (SMOTE) to handle class imbalance, Linear Discriminant Analysis (LDA) for feature extraction, and XGBoost for classification. There are 947 samples in the dataset, which are divided into nine different age groups. By creating synthetic samples for minority classes, SMOTE improves model performance and ensures balanced training. LDA facilitates effective data representation by lowering dimensionality while maintaining the most discriminative features, which enhances classification even further. After that, XGBoost is used to classify the retrieved features, utilizing gradient boosting to enhance classification accuracy and optimize decision-making. The suggested hybrid model outperforms traditional standalone techniques with a remarkable accuracy of 94.89%. These results demonstrate how data balancing, feature extraction, and machine learning classifiers work together to estimate age, providing a reliable and automated solution for use in forensic science, pediatric dentistry, and legal investigations.

Keywords: Age Determination, Forensic Analysis, Dental X-rays, Deep Learning Models, SMOTE, XGBoost, Machine Learning,Feature Extraction

1. Introduction

In the forensic discipline, estimating age is a crucial step. It is essential for identifying both living and deceased individuals [1]. Which can rebuild biological profiles for missing-person cases, verify the age of younger offenders, and provide assistance when personal documentation are not accessible [2].

Skeletal, odontological, ethnological, and intellectual methodologies can all be used to study an individual's development [3]. Compared to physical and skeletal maturity indicators, age assessment using radiographic tooth development is thought to be the most reliable method since it is mostly genetically determined and less impacted by environmental and nutritional factors [4].

Kvaal's method, which is defined by examining the regression of pulp size, is one of several techniques for calculating dental age based on the examination of the tooth pulp [5]. The most widely used method, the Demirjian technique, classifies teeth into eight groups (A–H) according to their level of calcification and maturity [6]. In order to allow for direct conversion from categorization to age, Willems et al. changed this approach and offered a new scoring system [7]. By measuring the open apices of seven permanent teeth in the left jaw on panoramic radiographs, Cameriere developed a European formula [8].

Nevertheless, these techniques are somewhat subjective, which results in a comparatively high degree of human error, and their use necessitates sufficient experience to reduce mistakes [9].

A significant development in forensic identification could come from artificial intelligence (AI), a branch of engineering research that teaches computers to solve problems and make decisions on their own. Data-driven techniques like machine learning and deep learning models, which are the foundation of state-of-the-art AI, have produced excellent outcomes for image analysis [10]. A few recent studies have tried to address the drawbacks of traditional approaches by combining machine learning algorithms with panoramic radiographs. These include the suggested modified conventional method with machine learning algorithms and an end-to-end system built on a convolutional neural network (CNN) model with raw panoramic radiographs [9][11].

The purpose of this research is to improve accuracy by creating an effective age determination method with machine learning methods, such as gradient boosting algorithms and deep learning models of CNN. The goal of this research is to increase the accuracy and dependability of determination of age from dental X-ray images by utilizing the advantages of gradient boosting for more effective decision-making and deep learning model for feature extraction. Through efficient feature representation and data preprocessing, the study aims to maximize model performance and eventually advance the fields of medical diagnostics and forensic odontology.

This research study includes an introduction explaining the importance of utilizing machine learning to determine age. Next, it reviews related studies and discusses the limits of current methods. The methodology section describes the dataset, preprocessing methods, and a proposed hybrid model that combines gradient boosting with deep learning. Results from experiments show the model's performance and comparison with current methods. The paper ends with key conclusions, possible uses, and future research avenues for enhancement.

2. Related Study

In this section, we review related studies on age determination using dental X-rays, focusing on existing approaches and their findings.

In order to extract features from panoramic radiographs and determine age, the study uses Two Dimensional Deep Convolutional Neural Networks (2D-DCNN) and One Dimensional Deep Convolutional Neural Networks (1D-DCNN). With a Mean Squared Error (MSE) of 0.00027 and an R^2 score of 0.999, it combines Genetic Algorithm (GA) and Random Forest (RF) to create a Modified Genetic-Random Forest Algorithm (MG-RF), which shows accuracy in age detection [12]. Expanding on deep learning-based analysis, it uses a score-level fusion approach to evaluate legal age using panoramic dental X-ray pictures of the inferior arch's third molars. Its function as a decision support tool for forensic experts was reaffirmed by testing 440 samples ranging in age from 15 to 22 [13]. Additionally, the effects of adding sex as a characteristic were investigated in a study comparing dental age estimating techniques. It was discovered that adding sex information to 1,734 panoramic radiographs of those ages 8 to 23 marginally decreased estimation errors for those ages 15 to 23, while the clinical impact was still negligible [14].

A two-stage method that integrated image classification with EfficientNetV2M and object recognition with Scaled-YOLOv4 advanced automated dental age computation. The technique demonstrated practical feasibility by successfully detecting dental germs and classifying developmental phases, with mean absolute errors ranging from 0.261 to 0.396 [15]. With a mean absolute error (MAE) of 1.08 years, a regression-based deep learning model that was trained on 14,000 images of teenagers between the ages of 11 and 20 outperformed manual estimating techniques [16]. Transfer learning-based deep learning models were investigated to improve forensic applications. A modified InceptionV3 model was tested on 1,332 dental panoramic radiography (DPR) images and showed reliability in determining age with an MAE of 3.13 and an R^2 of 87% [17]. This method was expanded by a multi-task CNN model called DeepToothDuo, which simultaneously predicted age and sex. It achieved an age prediction error of 1.96 years and enhanced model interpretability using SHAP analysis [18]. By combining CNNs for tooth development stage classification with LightGBM regression, machine learning approaches have improved age prediction even further. The model achieved an accuracy gain of 10.85 months by reducing estimating errors when compared to Demirjian's technique [19]. Statistical methods have also been used, such as the Active Shape Model (ASM) and Active Appearance Model (AAM), which analyze variations in the lower right third molar to predict age. The retrieved features were then processed using a Radial Basis Network, which improved the accuracy and consistency of forensic dental age prediction [20].

EfficientNet-B5 achieved a mean absolute error (MAE) of 2.83 and a root mean square error (RMSE) of 4.59, indicating the maximum efficacy in transfer learning for age estimation. The results demonstrated how morphological traits such the mandibular body, mandibular angle, maxillary sinus, and dentition affect age [21]. Five algorithms were used to further analyze 18 radiomorphometric features from panoramic radiographs. The results showed that the algorithms were highly accurate in classifying individuals into six groups based on 10-year intervals, especially in younger (AUC 0.85-0.88) and older (AUC 0.82-0.90) age groups [22]. The study on mandibular second and third molars employed Random Forest (RF) and Support Vector Machine (SVM) models to measure the root lengths of 1,000 radiographs taken by people between the ages of 12 and 25.The mesial root length of the right third molar is a crucial indication of age, and SVM had the highest classification accuracy of 86.4% [23]. With an accuracy rate of 84.3%, Convolutional Neural Networks (CNN) have also been used to analyze mandibular third molars in panoramic radiographs, confirming its potential for use in forensic and medical applications [24].

The significance of dental age over chronological age was highlighted by a regression model that was trained on panoramic radiographs and assessed ResNet50, VGG16, DenseNet121, and Xception. For ages 6–11, Xception produced the lowest error rate of 1.417 [25]. SqueezeNet, VGG19, ResNet152, and EfficientNet were evaluated in a study with 785 panoramic radiographs. VGG19 had the best accuracy of 92.95% in two-class classification, while EfficientNet did the best in the twelve-class scenario with 69.11% accuracy [26]. With a Test MAE of 3.1 years and an R2 of 95.5%, a comprehensive analysis of 12,827 X-ray images that included anatomical indications including pulp chamber diameters, tooth calcification phases, and mandibular characteristics showed great forensic applicability [27]. By using DenseNet169 on a dataset of 437 radiographs, additional efforts advanced automated age estimation by obtaining an R^2 of 0.57 and an MAE of 7.07, as measured by metrics such as MSE and MAPE [28].

3. Materials and Methods

The method used for age classification using dental X-ray images are described in this section. It describes the model architecture, assessment metrics, preprocessing method, and dataset.

3.1. Dataset Description

A total of 947 panoramic radiograph samples were gathered from three clinics located in Gujarat. Individual details including age, gender, and corresponding digital panoramic radiographs are included in the dataset. The images serve as a useful resource for dental and medical imaging research and analysis since they may be utilized to determine age based on radiographic features.

The dataset's overall sample distribution across classes is shown in Figure 1. The 947 samples in the dataset are divided into nine age-based classes, each of which includes a 10-year age range (e.g., 1-10, 11-20,..., 71-80,81-90).

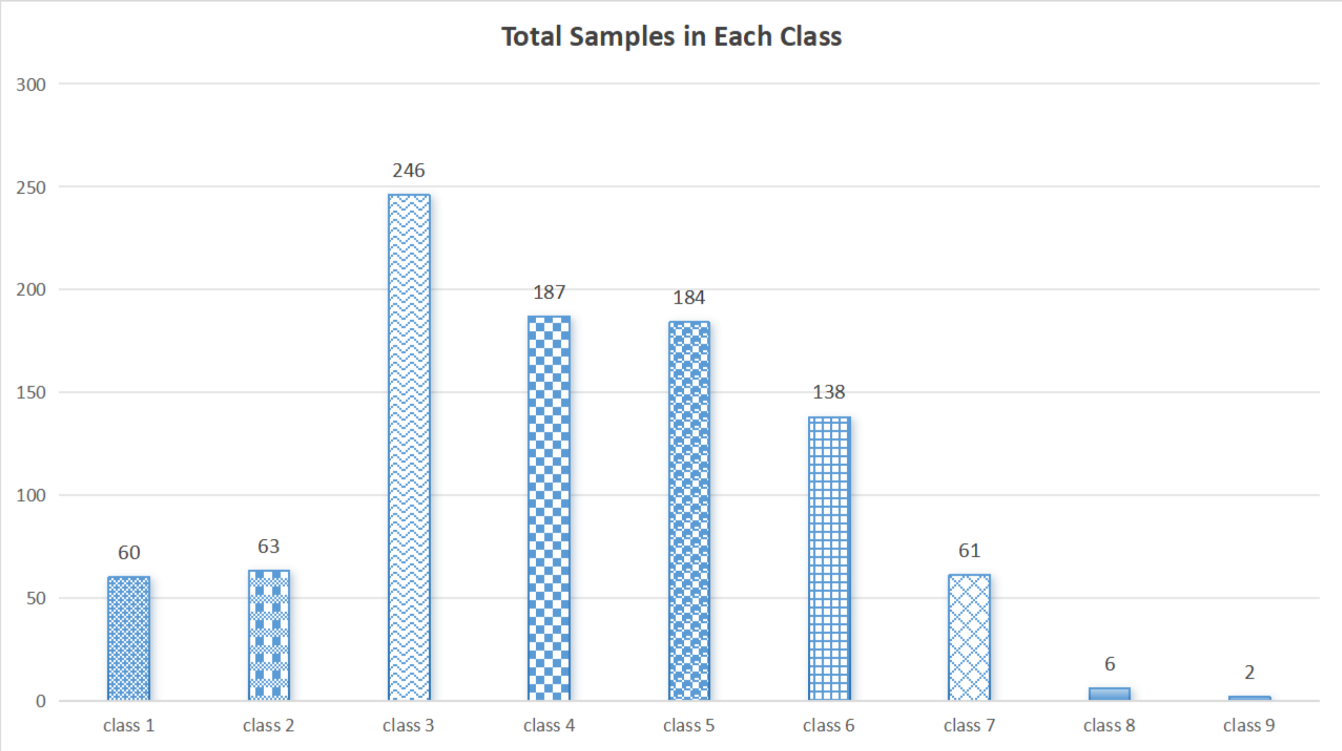


Figure 1 : Dataset Distribution

3.2. Proposed Methodology

An effective strategy for classifying dental ages using panoramic dental X-ray images is shown in Figure 2. Preprocessing the data, extracting features, addressing class imbalance, classifying using machine learning, and evaluating performance are some of the steps in the workflow.

Preprocessing is crucial for improving dental X-ray images and preparing them for feature extraction and classification. To ensure consistency in input size for training and testing, the first preprocessing step involves resizing each image to a given dimension. A bilateral filter is used to eliminate noise from the image while maintaining important edge features after resizing. By preserving important structures like dental roots and enamel, this process enhances the quality of feature extraction for accurate classification.

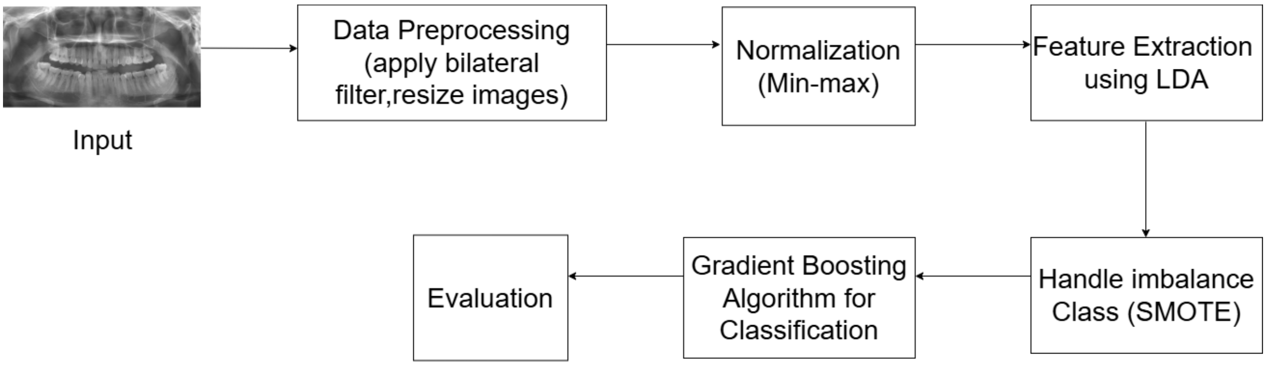


Figure 2 : Proposed Methodology for Age Classification

After preprocessing, the images are normalized using Min-Max scaling, which converts pixel intensity values to a predetermined range, usually 0 to 1. By ensuring that every image has a consistent distribution of intensity, normalization lowers numerical instability during training. Additionally, this phase speeds up the classification model's convergence and improves its capacity to extract significant features from the X-ray images.

To reduce dimensionality and preserve important information from the images, feature extraction is a crucial step. To identify the most discriminative features that facilitate age classification, this study uses Linear Discriminant Analysis (LDA). LDA minimizes the variance within a class while maximizing the variance between age groups. The classifier can differentiate between age groups more effectively due to this transformation. Each class's mean vectors are computed, within-class and between-class scatter matrices are calculated, and eigenvalues and eigenvectors are found to create a projection matrix. By projecting the original dataset onto this new feature space, the classification performance is significantly enhanced.

Imbalanced age group distributions, in which some age groups have much fewer samples than others, provide one of the difficulties in dental age classification. The Synthetic Minority Over-sampling Technique (SMOTE) is used to solve this problem. SMOTE creates synthetic samples by interpolating between existing instances, in contrast to conventional oversampling methods that replicate minority class examples. With this method, the dataset is balanced, the classifier is not skewed toward majority classes, and the model's capacity for generalization is enhanced.

To ensure a balanced distribution for model training and evaluation, the dataset is divided into 70% training and 30% testing. To avoid bias, the split is made at random while keeping the percentage of each class the same. To improve generalization, this enables the model to learn efficiently from training data while being evaluated on unseen samples.

The processed data is given into the Gradient Boosting Algorithm (GBA) for classification after feature extraction and class balance. Gradient Boosting is an ensemble learning strategy that builds a strong prediction model by gradually improving weak learners (decision trees). To reduce these errors repeatedly, the technique first trains a decision tree on the dataset calculates residual errors, and then trains more trees. Because the final model is an optimal blend of several trees, it guarantees great age classification accuracy.

XGBoost iteratively minimizes a loss function by employing gradient boosting to construct an ensemble of weak learners (decision trees). The primary concept is:

$$F_m(x) = F_{m-1}(x) + \gamma h_m(x) \quad (1)$$

where:

$F_m(x)$ is the model at step m

$F_{m-1}(x)$ is the previous model

$h_m(x)$ is the new weak learner (decision tree)

γ is the learning rate

Objective Function in XGBoost

The technique guides the model to achieve the optimal balance between accuracy and preventing overfitting by penalizing highly complex trees. The objective function combines the training loss with a regularization term, which the algorithm aims to reduce during training. There are two terms in that:

$$\mathcal{L}(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \qquad (2)$$

where :

$\mathcal{L}(\theta)$ is the total loss function that needs to be minimized.

$l(y_i, \hat{y}_i)$ is the loss function that quantifies the difference between the actual label y_i and the predicted label $\hat{y}_i$.

$\Omega(f_k)$ is the regularization term that penalizes the complexity of the model to prevent overfitting.

Loss function ($\mathbf{l(y_i, \hat{y}_i)}$) : For multi-class classification problems, XGBoost uses the softmax cross-entropy loss function:

$$\mathcal{L} = - \sum \sum y_{ij} \log(\hat{y}_{ij}) \qquad (3)$$

Where y_{ij} is 1 if sample i belongs to class j and $\hat{y}_{ij}$ is the predicted probability for class j.

Regularization term ($\mathbf{\Omega(f_k)}$) :

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} {w^2}_j \qquad (4)$$

Where γT is the number of terminal nodes (leaves), and w_j are the leaf weights.

Optimizing the XGBoost classifier for dental age classification requires hyperparameter adjustment. To effectively explore important parameters while balancing computational cost and performance, we utilize RandomizedSearchCV. Boosting rounds are controlled by the number of estimators n_estimators, which ranges from 200 to 600. Stable convergence is ensured by the learning rate learning_rate (0.01 to 0.3). Subsampling subsample and column sampling per tree colsample_bytree (0.7 to 1.0) add randomness to avoid overfitting, while tree depth max_depth (4 to 8) controls model complexity. Large weights are penalized by fine-tuning the regularization parameters L1 reg_alpha and L2 reg_lambda between 0.01 and 10, while gamma gamma (0 to 0.4) regulates tree splits to enhance model performance.

3.2.1.Evaluation of Model

Calculating the model's accuracy involves dividing the total number of samples by the number of accurately predicted samples. In terms of mathematics, it is provided by:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \quad (5)$$

Each class's precision, recall, and F1-score are included in the classification report. Recall measures how many actual positive samples were found, whereas precision measures how many predicted positive samples were truly accurate. The harmonic mean of recall and precision is the F1-score. The confusion matrix can be used to obtain each measure in the following ways:

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}, \quad \text{F1-score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \quad (6)$$

A heatmap is used to represent the confusion matrix, with off-diagonal portions signifying incorrect classifications and diagonal elements representing correct classifications. This aids in evaluating the model's performance and identifying areas in need of development.

4. Results

Using dental X-ray images, we evaluated several machine learning and deep learning models for age classification. Metrics for accuracy, precision, and recall were used to evaluate the models' performance. A comparison of various models is shown in Table 1.

Models	Accuracy	Precision	Recall
CNN	65%	75%	65%
Random Forest	83%	86%	83%
Naive Bayes	80%	82%	80%
SVM	83%	85%	83%
VGG16	57.34%	60.01%	57.34%
ResNet50	53%	54.23%	53%
EfficientNetB0	42.63%	43.20%	42.63%
DCNN	78.01%	80%	78.01%
VGG16 + XGBoost	78.35%	79.15%	78.35%
LDA+ XGBoost(Proposed)	**94.89%**	**94.96%**	**94.89%**

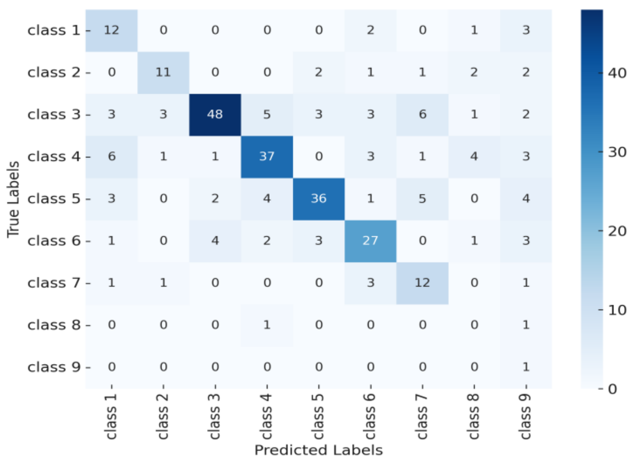
Table 1 : Performance Comparison of Different Methods for Age Classification

The accuracy of the Support Vector Machine (SVM) reached 83%, followed by Random Forest (83%) and Naive Bayes (80%) among conventional machine learning models. CNN (65%) and ResNet50 (53%) were among the deep learning-based architectures that showed varying results.

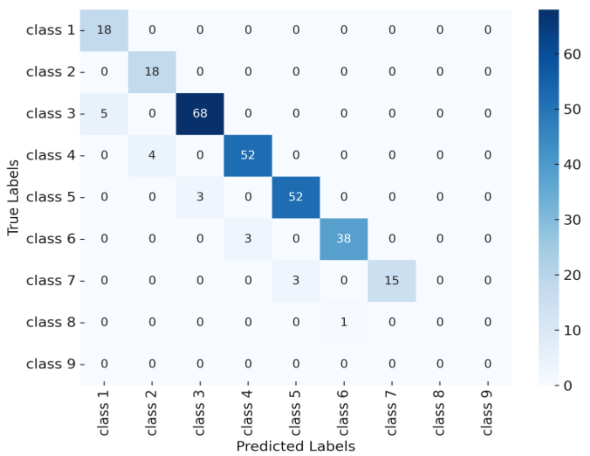
The commonly used deep learning architecture, the VGG16 model, had an accuracy of 57.34%; when combined with XGBoost, it somewhat improved to 78.35%. DCNN also obtained an accuracy of 78.01%.

The proposed hybrid method, LDA + XGBoost, performed better than any other model, attaining 94.89% accuracy, 94.96% precision, and 94.89% recall. The usefulness of using XGBoost for classification and

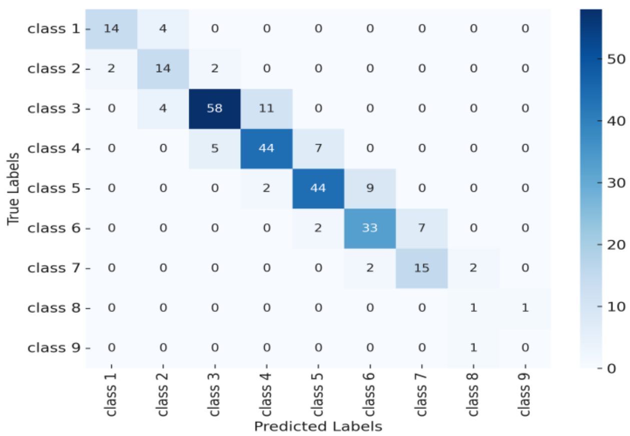
Linear Discriminant Analysis (LDA) for feature extraction is demonstrated by this notable increase.
The effective feature extraction capability of LDA, which reduces dimension while maintaining class separability, and the effective generalization ability of XGBoost are responsible for the proposed approach's better performance. Compared to traditional deep learning and machine learning models, the combination of these methods allows for more reliable age classification.
Overall, the findings show that age classification accuracy in dental X-ray analysis can be significantly improved by a hybrid model that combines feature extraction and ensemble learning techniques.
The confusion matrix for the various age classification methods is shown below. It highlights the model's performance with a thorough comparison of the actual and anticipated age groups. Whereas off-diagonal values signify misclassifications, diagonal values represent occurrences that were successfully classified.



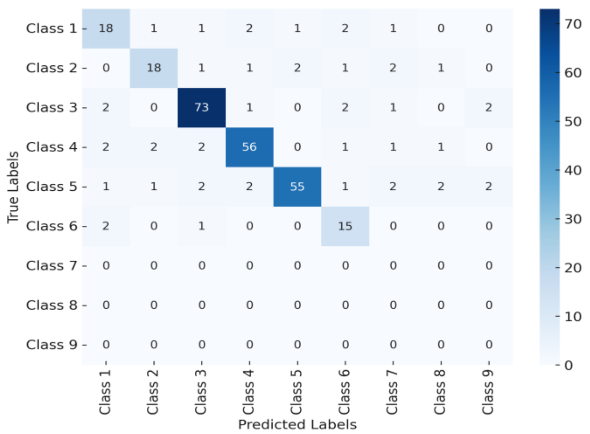
(a)



(b)



(c)



(d)

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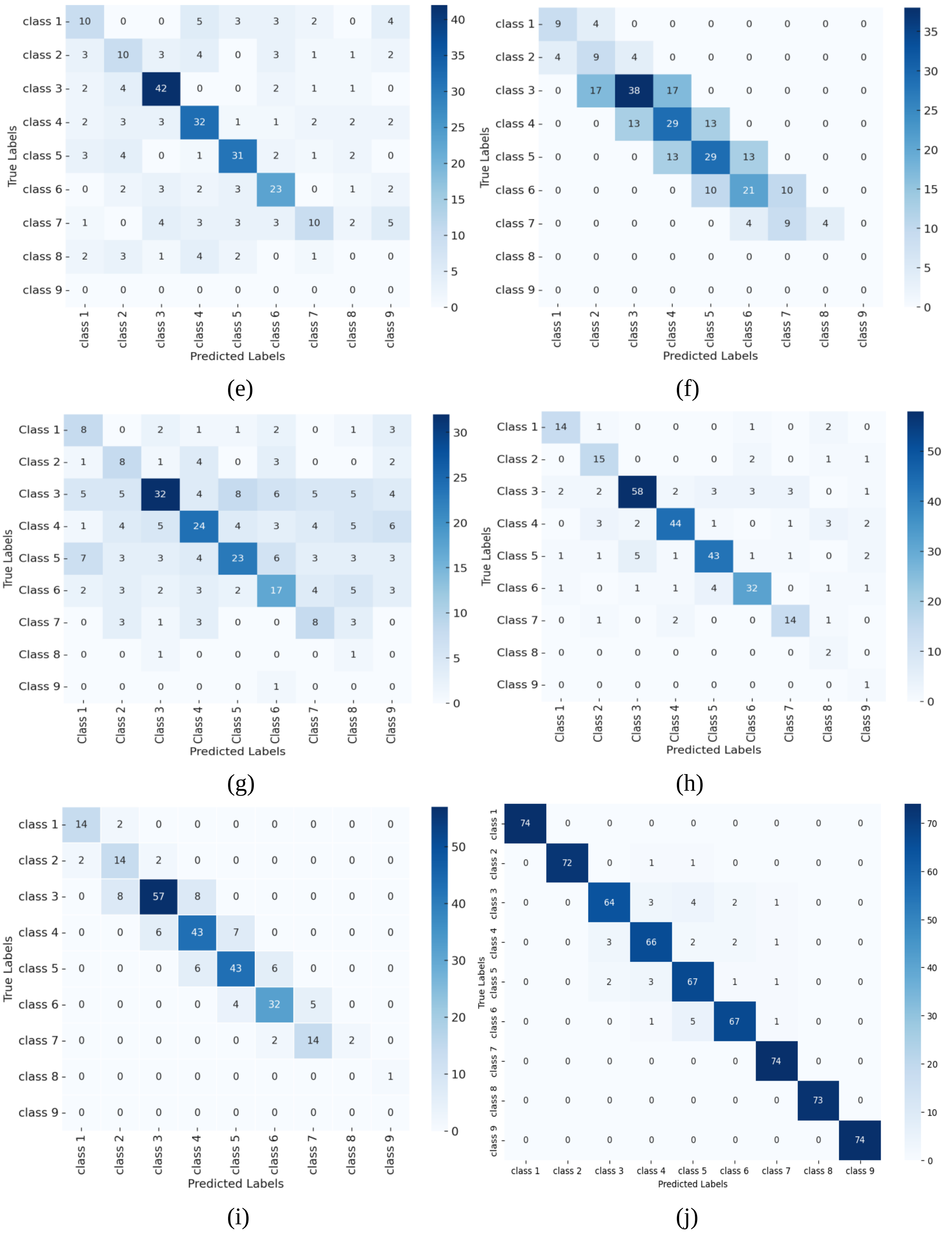

Figure 3 : Confusion Matrices for Age Classification Using Different Methods. (a) CNN, (b) Random Forest, (c) Naive Bayes, (d) SVM, (e) VGG16, (f) ResNet50, (g) EfficientNetB0, (h) DCNN, (i) VGG16+XGBoost, (j) LDA+XGBoost.

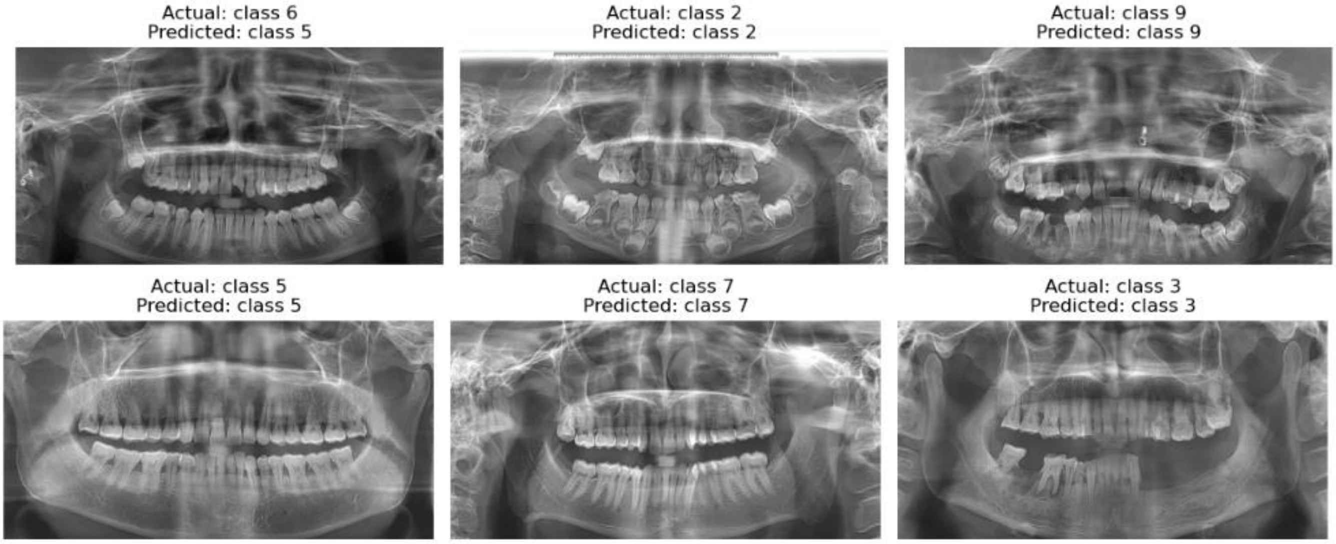

Figure 4 : Panoramic Radiographs With Actual vs. Predicted Labels.

5. Conclusion

In summary, our study demonstrates a thorough assessment of different deep learning and machine learning models for age classification using dental X-ray data. The accuracy levels of deep learning-based techniques like CNN, VGG16, and ResNet50 varied, while conventional models like SVM and Naive Bayes performed well. The efficiency of integrating feature extraction and ensemble learning techniques was demonstrated by the proposed LDA + XGBoost hybrid model, which achieved 94.89% accuracy, significantly outperforming all other methods. According to the findings, hybrid approaches that combine robust classification techniques with deep feature extraction can improve classification performance. By offering a very precise and effective model that may be useful in forensic and clinical settings, this study improves the field of dental age determination.

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