RESEARCH PAPER

Artificial Intelligence in Dental Shade Matching: A Narrative Review

Dr. Newbegin Gold Pearlin Mary[1*], Dr. Alagarswamy Venkatesh[2], Dr. Maniarasu Kalaiarasi[3], Dr. Maria Anisha Sebatni[4], Dr. Karthik Arumugam[5]

[1*]Professor, Department of Conservative Dentistry and Endodontics, Sree Balaji Dental College and Hospital, Bharath Institute of Higher Education and Research, Narayanapuram, Pallikaranai, Chennai - 600 100, Tamil Nadu, India

[2]Professor & Head, Department of Conservative Dentistry and Endodontics, Sree Balaji Dental College and Hospital, Bharath Institute of Higher Education and Research, Narayanapuram, Pallikaranai, Chennai - 600 100, Tamil Nadu, India

[3]Post Graduate, Department of Conservative Dentistry and Endodontics, Sree Balaji Dental College and Hospital, Bharath Institute of Higher Education and Research, Narayanapuram, Pallikaranai, Chennai - 600 100, Tamil Nadu, India

[4]Associate Professor, Department of Conservative Dentistry and Endodontics, Tagore Dental College and Hospital, Rathinamangalam, Chennai 600048, Tamil Nadu, India

[5]Professor, Department of Conservative Dentistry and Endodontics, Sree Balaji Dental College and Hospital, Bharath Institute of Higher Education and Research, Narayanapuram, Pallikaranai, Chennai - 600 100, Tamil Nadu, India

***Corresponding Author:**

Dr. Newbegin Gold Pearlin Mary

Professor, Department of Conservative Dentistry and Endodontics, Sree Balaji Dental College and Hospital, Bharath Institute of Higher Education and Research, Narayanapuram, Pallikaranai, Chennai - 600 100, Tamil Nadu, India

Email ID: drngoldpearlinmary@gmail.com

Abstract

Shade selection continues to be an important factor of esthetic success in restorative and prosthetic dentistry. The limitations of traditional optical shade matching—subjective perception, light variability, and metamerism—lead to inconsistent results and unhappy patients. Although instrumental techniques like colorimeters and spectrophotometers increased reproducibility, they are still expensive and technique-sensitive. Artificial intelligence (AI) and machine learning (ML) have become revolutionary techniques in recent years for automating and standardizing dental shade matching through the analysis of optical and image-based data. Under controlled conditions, Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and fuzzy logic systems have shown potential accuracy in tooth shade prediction that is comparable to instrumental approaches.The underlying principles of color science are described, current algorithms and approaches are assessed, and their clinical viability, limitations, and future prospects are discussed in this narrative review, which also synthesizes information from recent research on AI applications in dental shade matching. Prior to clinical translation, problems including dataset bias, illumination standardization, device calibration, and regulatory validation must be resolved, notwithstanding AI's great potential for objective, repeatable, and easily accessible color assessment.

Keywords: deep learning, machine learning, smartphone, colorimetry, spectrophotometer, artificial intelligence, shade matching, and dentistry.

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Introduction

When it comes to the aesthetic integration of dental restorations with the surrounding dentition, color perception is crucial. Errors in shade matching are a major cause of degraded aesthetics, patient unhappiness, and prosthetic remakes[1],[2]. Although technology has advanced, the most common clinical method is still visual shade selection utilizing shade guidelines like the VITA Classical A1–D4 [3]. However, visual approaches are subjective by nature and are affected by viewer experience, metamerism, operator tiredness, and ambient lighting.[4],[5],[6]As a result, observers rarely agree more than 50% of the time.[7]

By measuring color in standardized color spaces like CIELAB, instrumental techniques like spectrophotometers, colorimeters, and intraoral scanners have decreased subjectivity. [8],[9] These devices are costly, sensitive to environmental influences, and need to be calibrated even if they increase accuracy and reproducibility[10],[11],[12]. Research on digital and AI-based shade-matching technologies that can analyze teeth photos taken by clinical cameras or smartphones has increased due to the need for systems that are accurate, affordable, and easy to use [13], [14],[15],[16] .

Pattern identification and image analysis in medicine and dentistry have been transformed by artificial intelligence, which includes Machine Learning (ML) and Deep Learning (DL). [17] AI can forecast tooth shade or correct color in restorative dentistry by extracting color, texture, and illumination information from digital photos. [18],[19] Convolutional Neural Networks (CNN), a type of deep neural network, have demonstrated promise for automated, repeatable shade analysis on par with the gold standard of spectrophotometric measurements [20–23]. Although there are still issues with dataset variability, lighting consistency, and clinical validation, systematic evaluations have proven that AI systems are becoming more accurate at predicting dental color [24–26].

The principles, clinical uses, limitations, and future research directions of AI systems in dental shade matching are all covered in this review, which incorporates the most recent data from several literature sources.

Fundamentals of Color Science in Dentistry

The CIE LAB* color space, created by the International Commission on Illumination (CIE), is a quantitative representation of color in dentistry. It divides color into three categories: lightness (L*), red–green axis (A*), and yellow–blue axis (B*). [27] ΔE metrics are used to express the differences between two colors. When compared to previous ΔE*ab metrics, the CIEDE2000 formula offers a better correlation with human visual perception. [28, 29] Clinically, values up to 3.3 are regarded as clinically acceptable, while $\Delta E_{00} \leq 1$ is typically regarded as unnoticeable . [30–32]

When comparing instrumental or AI-based color measurements to reference standards like spectrophotometers, dental researchers utilize ΔE metrics.[33] Standardized lighting (usually D65 daylight illumination), accurate camera calibration, and neutral backgrounds to reduce perceptual distortion are necessary for reliable assessment[34], [35] .When assessing AI-based systems, ΔE_{00} levels are used as the standard for reproducibility and performance.

Environmental and physiological factors limit human color perception. High inter- and intra-observer variability is caused by factors such as observer fatigue, experience, and ambient lighting [36]. Shade communication is further complicated by the phenomena of metamerism, in which two colors appear the same under one light source but different under another [37]. Therefore, objective, automated techniques that can account for these differences are very important from a therapeutic standpoint.

Traditional and Digital Shade-Matching Approaches

1. Visual Techniques

In clinical practice, visual shade selection using standardized shade guides continues to be the preferred approach. [38] A variety of tabs indicating tooth hues based on hue, chroma, and value are available in the popular VITA Classical and VITA 3D-Master systems.[39]Disparities in translucency between guide tabs and enamel, limited coverage of the natural tooth color space, and clinician heterogeneity in perception are some of the limitations.[40], [41]According to studies, depending on lighting conditions and observer expertise, inter-examiner agreement in visual shade matching can range from 25% to 50% . [42],[43]

2. Instrumental Approaches

Tooth color can be quantitatively analyzed using instruments like spectrophotometers, colorimeters, and spectroradiometers [44] Spectrophotometers give highly reproducible CIELAB coordinates and measure reflectance throughout the visible spectrum. [45], [45],[46],[47] Although they make measuring easier, colorimeters and intraoral scanners with color sensors are less perceptive of subtleties in the spectrum[48],[49] Instrumental approaches are more accurate and consistent than visual methods, according to comparative evaluations. [50],[51],[52]

The high cost, intricate calibration requirements, and restricted accessibility in standard clinical settings are practical disadvantages of these equipment.[53],[54] Furthermore, measurement disparities may be introduced by variations in light geometry, aperture geometry, and device variability. [55],[56]

3. Digital Imaging and Smartphone-Based Systems

Accessible color data is provided by digital photography, especially with cellphones and intraoral cameras.[57],[58] Inconsistent results, however, may arise from uncontrolled illumination, exposure settings, and sensor variations [59]. Reliability is increased through calibration with standardized lighting and color reference cards [60]. In order to improve color prediction accuracy and account for light variations, recent improvements combine digital imagery with AI-based analysis [61],[62],[63].

Artificial Intelligence in Dental Shade Matching

1. Overview of AI and Machine Learning in Dentistry

Artificial intelligence (AI) refers to computing systems that mimic cognitive capabilities including learning, reasoning, and pattern recognition.[64] AI has been used in dentistry for CAD-CAM design optimization, implant identification, endodontic diagnosis, and caries detection.[65],[66],67],[68] AI algorithms use image-based or numerical inputs to forecast tooth color classes that match established shade guides in the context of shade matching. [69],[70]

While deep learning (DL), a subset of machine learning (ML), uses multilayered neural networks that can extract features on their own, machine learning (ML) algorithms use patterns in data to predict outcomes.[71],[72],[73] Dental shade-matching research is dominated by supervised learning, in which models are trained on labeled datasets (pictures with known colors) to classify or regress color outputs. [74]

2. Classical Machine-Learning Approaches

Traditional machine learning methods like support vector machines (SVMs), decision trees (DTs), random forests (RFs), k-nearest neighbor (KNN), and fuzzy-logic systems were used in early digital shade-matching experiments. [75], [76],[77], [78], [79]

a. By applying membership functions to linguistic shade factors, fuzzy-logic systems were able to quantify visual perception uncertainty with accuracies of 92% in in-vitro datasets [80].

b. Back-propagation neural networks (GA + BPNN) in conjunction with genetic algorithms enhanced weight parameter optimization and produced reduced mean-square-error values. [81]

c. When cross-validated, Support Vector Machine (SVM) based classifiers with features from CIELAB and HSV spaces achieved up to 97% accuracy. [82]

When it came to leucite-based ceramic color prediction using spectral input, decision-tree regression had the best recorded accuracy (99.7%). [83]

d. All of these techniques demonstrated that feature representation and algorithm choice have a significant impact on prediction performance .[84]

3. Convolutional Neural Networks and Deep Learning

Convolutional Neural Networks (CNNs) became the most popular architectures for color analysis as processing capacity increased. CNNs eliminate the requirement for manual feature engineering by automatically learning chromatic and spatial features from dental pictures .[85],[86]

Depending on dataset size and illumination control, studies using CNNs on annotated dental pictures obtained classification accuracies ranging from 68% to 97%.[87],[88] Additionally, maxillofacial silicone hues with $\Delta E < 3.5$ have been predicted using hybrid deep models, such as Artificial Neural Networks (ANNs) and Attention-Based Gated Recurrent Units (Att-GRU).[89]

Under standardized illumination, AI systems that were trained on sizable smartphone datasets utilizing RGB and HSV color characteristics and improved using random-forest or gradient-boosting algorithms (XGBoost) showed prediction accuracy levels of over 97%.[90] Prior to shade estimate, automated dental region segmentation was made possible by the integration of You Only Look Once (YOLO) object-detection frameworks.[91]

4. Datasets, Feature Extraction, and Validation Metrics

AI shade-matching model performance is heavily reliant on preprocessing and data quality. Datasets used in studies range from over 15,000 tooth images to 26 shade tabs. [92] RGB, HSV, and CIELAB color models are frequently used in feature extraction; of these, CIELAB most closely resembles human perception and is still the standard for ΔE evaluation. [93],[94]

The ratios of training to testing range from 70:30 to 80:20, and some include k-fold cross-validation to lessen overfitting. [95] Accuracy, Mean Absolute Error (MAE), Root-Mean-Square Error (RMSE), and perceptual thresholds like $\Delta E00 \leq 3.3$ are examples of evaluation metrics. [96],[97] Comparative findings show that trained neural networks can approach the perceptibility threshold [98] by achieving mean ΔE differences below 2.0.

Evidence from Systematic Reviews

In 2024, *Shetty et al*. conducted a systematic review of 15 research (2010–2023) that included several AI algorithms, such as fuzzy logic, ANN, CNN, KNN, SVM, and decision-tree regression. [99] The analysis came to the conclusion that accuracy is greatly impacted by lighting circumstances, device type, and color-space model, with knowledge-based and neural-network systems outperforming others.

AI-driven shade matching significantly lowers operator bias and enhances repeatability when compared to visual approaches, according to recent reviews and meta-analyses. [100],[102],[103] However, meta-analytic pooling is not possible due to methodological heterogeneity.

The gold-standard comparators for confirming AI predictions are still instrumental standards like spectrophotometers. [104]

Clinical Accuracy and Comparative Performance

Artificial intelligence (AI)-based solutions frequently approach spectrophotometer accuracy (ΔE = 1-2 units) when tested under controlled illumination and standardized photography. [105] For instance, when compared to VITA Easyshade measurements, smartphone-based SVM classifiers achieved 97–100% accuracy. [106] The results of spectrophotometers showed a significant correlation ($r > 0.9$) with CNN models that integrated preprocessing (exposure normalization and white-balance correction). [107],[108]

Nevertheless, performance decreases ($\Delta E > 4$ units) with heterogeneous devices or under non-standard situations. [109] Therefore, for dependable results, protocol standardization—controlled distance, lighting (D65 illumination), cross-polarization, and reference color cards—is required. [110],[111],[112]

Discussion

One of the most subjective procedures in restorative dentistry can now be automated and objectiveized thanks to AI algorithms. These technologies reduce observer fatigue and metamerism effects by converting RGB or spectral data into perceptually accurate CIELAB coordinates. [113],[114],[115] In addition to adaptively learning intricate color connections that classical regression is unable to capture, neural networks mimic human pattern-recognition processes. [116]

Chairside, affordable color determination is made possible by integrating smartphone cameras with cloud-based AI frameworks (e.g., DentShadeAI prototypes).[117],[118] Through the use of standardized color data and visuals, these models facilitate digital communication with laboratories and real-time decision-making. [119]

Variability in illumination is still a significant confounding factor. If input data is not calibrated, spectral distortions cannot be completely corrected by even the most advanced networks. [120] Thus, the optimal balance between efficiency and reliability may now be provided by hybrid procedures that combine confirmatory spectrophotometer measurements with AI pre-analysis. [121],[122]

Challenges and Limitations

Generalizability and Dataset Bias: External validity was hindered by the majority of studies' use of small, region-specific datasets (less than 100 participants) with little ethnic and age diversity.[123], [124]

Illumination and Metamerism: Training data from several illuminations is necessary; AI predictions deteriorate with irregular light spectra. [125]

Device Calibration: The spectrum sensitivity of camera sensors varies greatly among smartphones; inbuilt calibration modules or device-agnostic models are required. [126],[127]

Regulatory and Ethical Considerations: Clinical certification requires performance reporting, algorithm explainability, and transparency in training data .[128]

Workflow Integration: AI-generated CIELAB coordinates, lab software, and shade-communication protocols must all be in harmony with digital prescriptions.[129]

Future Perspectives

To increase generalizability, the next stage of study should concentrate on creating sizable, annotated, multicenter datasets that cover a range of demographics, lighting scenarios, and device kinds.[130] Techniques for domain adaptation and cross-device standardization could lessen the need for calibration.[131] Enhancing reliability and facilitating regulatory approval are two benefits of integrating spectrophotometric ground truth during AI model training.[132] By giving physicians clear insights into algorithmic decisions, emerging techniques like explainable AI (XAI) can foster accountability and trust .[133] Transfer learning and few-shot learning might make it possible to adjust to new hues or devices using little data .[134] Hybrid systems that combine instrumental verification and AI-based pre-assessment could maximize workflow efficiency in the clinical setting while preserving accuracy.[135] The development of open-access repositories and uniform review methodologies requires interdisciplinary cooperation between dental researchers, computer scientists, and industry partners.[136] Lastly, for AI-based color devices to be widely used in restorative dentistry, regulatory guidelines under ISO or ADA frameworks must be established.[137],[138], [139], [140]

Conclusion

A promising addition to objective, repeatable, and effective dental shade matching is artificial intelligence. Under regulated conditions, AI algorithms in particular, neural networks, fuzzy systems, and support vector machines an attain predictive accuracy similar to spectrophotometric standards, according to evidence from both in-vitro and clinical investigations.
However, clinical translation is still constrained by differences in lighting, device calibration, and dataset heterogeneity. Standardized picture capture, transparent training datasets, clinically validated ΔE thresholds, and easy interaction with digital laboratory operations must be given top priority in AI development if it is to move from research to everyday application.
AI has the potential to revolutionize dental color science and improve aesthetic results for patients everywhere, provided that algorithm robustness and regulatory monitoring continue to improve.

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