Hybrid Learning System-Based Dental Caries Detection in X-Ray Images: Comparing Accuracy with Support Vector Machine

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Abstract: The primary objective of this study is to conduct a comparison between the accuracy of Support Vector Machines (SVM) and a Novel Hybrid Learning System (Novel HLS) for the detection of dental caries in dental photos obtained from a dedicated dataset. In this investigation, a total of 86 samples were gathered and divided into two distinct groups. Specifically, Group 1 comprised 43 samples that were processed using the Novel HLS approach, while Group 2 consisted of 43 samples that underwent processing with the SVM method. The dataset was imported as per the research protocol, and the Novel HLS code was developed employing Google Colab software. To determine the sample size, an online statistical analysis tool was employed, aiming for an 80% pretest power and an alpha value of 0.05. The sample size was calculated based on prior research findings. Results revealed that SVM achieved an accuracy rate of 70.816%, while the novel HLS method demonstrated a significantly higher accuracy of 97.221%. A statistical significance level of 0.012 ($P < 0.05$) indicated that there exists a noteworthy disparity in accuracy between the two methods. The dataset substantiates the observation that the Novel HLS approach outperforms SVM by a significant margin in terms of its predictive capabilities for dental caries detection.

1 INTRODUCTION

A condition affecting millions of individuals is known as dental caries, which entails the gradual deterioration of tooth structure. The terms "normal," "mild," "moderate," or "severe" dental caries denote the extent to which the condition has progressed (Machiulskiene 2019). "Normal" dental caries signifies the initial stage of the condition. Detecting dental caries at an early stage might obviate the need for more invasive surgical procedures, resulting in substantial long-term savings. In the realm of biological applications, bitewing radiography is considered the preferred approach for identifying demineralized proximal caries. Such caries are notoriously challenging to diagnose using clinical methods alone (Abzenada 2019). Combining bitewing radiography with a comprehensive visual examination can facilitate the relatively straightforward diagnosis of proximal caries. Additionally, technologies like fibre optic transillumination and DIAGNOdent, which are based on fluorescence, offer alternative means for detecting dental cavities.

The decayed missing filled teeth index (DMFT) is a pivotal metric for assessing caries-related conditions, relying on demographic data (Abuzenada 2019, Irfan 2020). This index allows the determination of the proportion of permanent teeth affected by caries. Recognizing that a variety of factors, including inadequate oral hygiene practices, poor dietary habits, dental interventions, and financial constraints, can influence oral health, establishing the DMFT and understanding associated risks becomes a crucial initial step in constructing personalized oral preventive strategies.

Article 9 of the legislation governing oral health in Korea mandates the implementation of surveys concerning the biomedical oral health of children (Hu et al. 2014). These surveys are conducted within Korea.

Previous studies have demonstrated that a total of 5880 papers from the biomedical survey have been published on IEEE Xplore since 2021, each offering distinct advantages. Within this context, it has been observed that 5880 articles related to the biomedical survey have been made available on IEEE Xplore. While methods relying on electrical resistance and teeth self-fluorescence seem most promising for

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accurately detecting early stages of enamel demineralization, it's worth noting that the dataset contains 5880 articles from the biomedical survey as well.

For this particular research, the creation of train and test datasets was undertaken by researchers using a dataset comprising 3000 periapical radiography images, divided in an 80:20 ratio. This split ratio was implemented using a GoogleNet Inception v3 CNN network, previously trained (Prakash et al. 2019), for pre-processing and transfer learning. A comprehensive assessment encompassing unique accuracy, reactivity, specificity, positive and negative predictive values, area under the curve (AUC), and ROC was carried out for both observation and separate DCNN algorithm execution, determined through a sequence of calculations (Loan et al. 2022).

The distribution of the 3000-image collection indicated that premolars were present in 25.9% of the maxilla and molars in 25.6% of the mandible. Based on diagnosis, the same dataset was categorized into non-dental caries (premolars: 26.1%, molars: 24.3%) and dental caries (premolars: 23.9%, molars: 25.7%). Notably, caries originating outside the teeth were more prevalent in premolars compared to those arising within the teeth.

Subsequently, the entire image collection was resized to dimensions of 299 by 299 pixels and stored in JPEG format (Almasri et al. 2019). In our technologically advanced society, X-rays find diverse applications, and in the context of this article, we will limit the discussion to their significance in medicine. The interpretation of X-rays holds particular importance in disease prevention and diagnosis due to its potential for unveiling concealed abnormalities. X-rays have been a vital tool in medical imaging since Rontgen's discovery of their ability to differentiate various bone structures (Bowling et al. 2002).

The presence of noise poses challenges in current biological data processing approaches, and the research's core aim is to employ Novel HLS for the detection of dental caries in X-ray images, enhancing accuracy, and subsequently comparing the outcomes with those obtained through the utilization of SVM.

2 MATERIALS AND METHODS

Each category is composed of a total of 43 distinct examples for selection. Group 1 samples were generated through the utilization of the unique HLS methodology for training, while Group 2 samples were trained using the well-established SVM classifier. Both training methodologies were harnessed to compose the samples.

The research is being conducted using a computer equipped with a 1024 by 768 pixel resolution screen, a 64-bit central processing unit, and 8 gigabytes of random access memory. The compilation of the Novel HLS code was executed using the Google Colab platform. Once the program was made publicly available, a training session was conducted on the dataset pertaining to dental caries. Subsequently, testing was carried out using the trained data. A comparison was drawn between the accuracy achieved by the Novel HLS and the accuracy attained by the currently employed SVM classifier.

The evaluation of performance hinges on the accuracy values obtained through the investigation. Upon completing the analysis, the dataset underwent data visualization. Following this stage, preprocessing of the dataset occurred, involving the removal of any erroneous or noisy data it may contain. The ultimate step involves the assessment of the findings' reliability.

A hybrid learning system designed for dental caries detection integrates various approaches, blending traditional image processing techniques with modern machine learning methods. This integration aims to enhance the accuracy and efficiency of identifying dental caries in dental photographs, ultimately improving the diagnostic process. Various imaging tools such as X-rays, intraoral cameras, and 3D scans can aid in diagnosing dental caries, commonly known as tooth decay or cavities. To construct a hybrid learning system for dental caries detection, the following steps can be outlined. Collect a diverse set of dental photographs, including images of healthy teeth and those affected by caries. Preprocess these images by enhancing contrast, reducing noise, and standardizing image quality. Accurate input data is crucial for the hybrid learning system's effectiveness. Employ traditional image processing methods to extract relevant features from dental images. Techniques like edge detection, texture analysis, and morphological operations can be used to highlight areas of interest such as cavities or enamel demineralization. Convert the extracted features into a suitable format for machine learning algorithms. This might involve vectorization or encoding to make the data understandable by machine learning models. Train machine learning models using the transformed features as input. Models like Convolutional Neural Networks (CNNs) and hybrid architectures are effective in recognizing complex patterns and relationships in data, enabling accurate predictions about dental caries onset. Transfer learning can further enhance accuracy by fine-tuning pre-trained models with dental imaging data. Combine predictions generated by multiple machine learning models to create an ensemble that surpasses the performance of individual models. Ensemble methods such as bagging and boosting can significantly enhance the overall performance and robustness of the caries detection system. Validate the hybrid learning system's performance using clinical data and annotations provided by subject matter experts. Fine-tune the system based on feedback from dental professionals to improve accuracy and clinical usefulness. Integrate the developed hybrid learning system with existing dental software or imaging systems for seamless incorporation into dental practices. Design a user-friendly interface that allows dentists to submit photographs and receive diagnostic results efficiently. Maintain an updated and enhanced hybrid learning system by incorporating new data, advancements in image processing and machine learning, and feedback from dental practitioners. This iterative process ensures the system's ongoing performance and relevance. By combining the strengths of both traditional image processing techniques and modern machine learning methods, a hybrid learning system can offer more accurate and efficient dental caries detection, contributing to improved patient care and diagnosis.

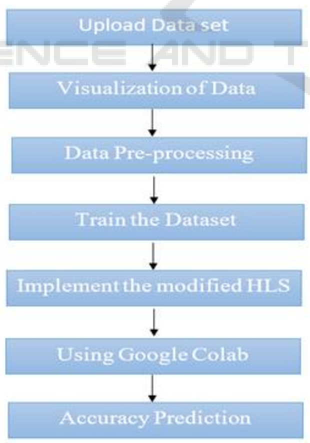

Figure 1: Process flow the accuracy finding using modified Novel HLS.

Google Colab, the platform where the Novel HLS algorithm is implemented (Acharya et al. 2018), provides the software for utilizing the Novel HLS algorithm. A hybrid learning system refers to the integration of two distinct algorithms in a way that the combined output exhibits superior accuracy. It employs supervised deep learning techniques like Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) for both regression and classification tasks. CNN and SVM are the two primary methodologies employed. The k-nearest neighbors algorithm (KNN or k-NN) is a supervised learning classifier that predicts the classification of a single data point based on its neighbouring data points. It generates predictions or classifications by considering the outcomes of this analysis. This approach is commonly known as KNN or k-NN. To achieve a higher level of accuracy by combining two distinct algorithms, it's a common approach to utilize hybrid learning systems. These systems employ supervised deep learning techniques, such as Convolutional Neural Networks (CNN) and Support Vector Machines (SVM), for both regression and classification tasks. CNN and SVM serve as the primary methodologies in this context.

A CNN possesses the ability to automatically extract relevant information from its input through a series of hierarchical convolutional layers. This distinctive capability sets CNNs apart from other types of neural networks. These convolutional layers often consist of multiple filters or kernels that analyse the input data to generate feature maps. These feature maps highlight patterns and edges present in the input data, whether in the form of text or images. The input data can be sourced from text files or image files.

In a hybrid deep learning network, the conventional CNN softmax layer is substituted with a non-linear SVM-based classification layer. This layer is integrated into the network structure to optimize the utilization of acquired features and enhance overall network stability. This modification aims to improve the network's performance by harnessing the strengths of both CNN and SVM techniques.

The project's proposed workflow is illustrated in Figure 1. Google Colab plays a crucial role within this workflow, as a specific step involves the utilization of Colab-generated code to implement a dataset. Once the dataset is imported and visualized, the subsequent stage entails data preparation. In this phase, the error figures from Google Drive are cross-referenced with the mounted code. Following the completion of this stage, the accuracy of the dental caries detection system employing SVM is evaluated and juxtaposed against the accuracy of an existing classifier referred to as KNN.

3 STATISTICAL ANALYSIS

The validity of the proposed study and the research methodologies utilized previously were assessed using the SPSS software program. In this study, the mean accuracy scores were the dependent variables, while the independent variables were the caries images. The level of significance was ascertained through the application of a T-test for independent samples.

4 RESULTS

Fig. 2. Statistical analysis using SPSS tool to find the accuracy of the caries dental in x-ray image Table 1 depicts a Bayesian analysis of the coefficient, wherein accuracy serves as the dependent variable and the model is predicated on groups. The analysis assumes standard reference priors and a data variance of 0.000. The table provides the mode and mean values for the data, along with a credible interval computed at a 95% confidence level. This interval denotes the upper and lower limits for the groups. Table 2 presents a contrast between the Novel HLS and SVM classifiers. The findings reveal that the Novel HLS classifier demonstrates a superior mean value of 97.432, in comparison to the SVM classifier with a mean value of 70.816, based on testing with a group of 43. It was ascertained that the means for each classifier exhibit distinct standard deviations.

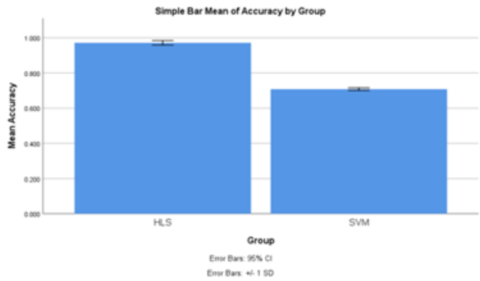

Figure 2: Displays a bar chart comparing Novel HLS and SVM accuracy. Novel HLS exhibits significantly higher accuracy (approximately 97.221% + 2%) than SVM (about 70.816% + 2%), with a 95% error bar.

Table 3 showcases the execution of an independent sample T-test for two groups. The outcomes indicate a significant disparity between the two groups concerning accuracy, showcasing a mean difference of 26.3674 and a standard error difference of 0.002280. The T-test yields a value of 115.638, signifying that the variance between the means of the two groups possesses statistical significance, with a probability (P) of less than 0.05.

Table 1: Bayesian estimation of coefficient.

Groups	Mode	Posterior Mean	Variance	95% Confidence Interval Lower Bound	95% Confidence Interval Upper bound
Novel HLS	97.651	97.651	.000	97.3	98.0
SVM	70.816	70.816	.000	70.5	71.1

Table 2: T-test compares the Novel HLS and the SVM classifier.

	Groups	N	Mean	Std.Deviation	Std.Mean Error
Accuracy	Novel HLS	43	97.221	0.12893	.001966
	SVM	43	70.816	0.7572	.001155

Table 3: Independent sample test.

		F	sig.	t	dif	sig(2-tailed)	Mean diff	Std.Error Difference	Lower	upper
Accuracy	Equal Variance Assumed	17.649	.032	115.638	84	.012	26.3674	.002280	25.9140	26.8209
	Equal Variance assumed			115.638	67.890	.012	26.3674	.002280	25.9124	26.8225

5 DISCUSSION

A substantial accuracy discrepancy of 97.22% was observed between the SVM classifier and the Novel HLS algorithm in accurate data prediction. The Novel HLS approach outperformed the SVM classifier notably. In contrast to the SVM classifier's accuracy rate of 70.816%, the Novel HLS method achieved a significantly higher accuracy rate of 97.221%. The observed variation in accuracy holds statistical significance, as indicated by a significance value of 0.012 ($P < 0.05$) derived from an independent variable test conducted using the SPSS IBM tool. This outcome lends weight to the inference that the observed distinction is statistically meaningful.

Other researchers have reported similar findings, and the goal of this study is to highlight the latest advancements in employing neural networks for the detection and diagnosis of dental caries. The study delved into research on diverse aspects of neural networks, including network types, database attributes, and outcomes. Moreover, the assessment explored how each study defined and categorised caries, considering various parameters such as caries type and the teeth examined (Nanmaran et al. 2022, Thakur et al. 2024). A precise definition of caries and the types of lesions under investigation is crucial before evaluating and comparing research outcomes. Caries refers to a form of dental decay. Studies employing ICDAS II displayed accuracy ranging from 80 to 88.9% (mean SD of 85.45 6.29%). However, research that defined caries as the loss of mineralization (radiolucent) achieved an accuracy of 97.1%. In this study, caries was defined as the loss of mineralization. Nonetheless, 76% of the papers assessed for this review omitted information about caries lesion definitions. Another potential bias source is the dataset used for training. The biomedical images employed in training need specialist annotations (Musri et al 2021). Seven of the analysed studies acknowledged the involvement of examiners in annotating images, though the level of expertise and number of examiners varied between investigations (Manzey et al 2006).

Studies have explored the correlation between dental experience and caries identification. Bussaneli et al. concluded that the examiner's expertise didn't impact the detection of occlusal lesions in primary teeth, but it did affect prioritization of treated lesions. An artificial intelligence's performance is restricted by the quality of input based on human observer ratings. Articles in this review's scope of examiner-assisted accuracy had a mean standard deviation of 88.7 8.55%, ranging from 80 to 97%. Results from research involving four specialists examining images yielded the second-best outcomes, followed by a single examiner using standard criteria for caries identification. Conversely, the least accurate findings emerged from research with two different examiners (Budd 2017). Only one study provided information on researchers' years of expertise, but since these findings weren't closely correlated with the total number of examiners (Parziale 2016), it's vital to consider other factors such as neural network usage, dataset, and caries definition. Training images can be time-intensive, potentially impacting accuracy in some scenarios. This limitation of the study is mitigated by selecting only necessary database image features for classification, significantly reducing training time. Consequently, the potential use of larger datasets for research becomes viable.

6 CONCLUSION

Based on the results obtained, the Novel HLS algorithm demonstrated superior accuracy compared to the established SVM classifier. The research findings clearly indicate that the Novel HLS algorithm outperforms the SVM classifier in accurately predicting data. The accuracy achieved by the Novel HLS algorithm is notably higher, at 97.22%, whereas the SVM classifier achieved a comparatively lower accuracy rate of 70.816%.

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