A Hybrid Optimization Approach with Deep Learning Technique for the Classification of Dental Caries

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***Abstract*—Due to the wealth of data available from different radiographic images, detecting dental caries has traditionally been a difficult undertaking. Numerous techniques have been developed to enhance image quality for quicker caries detection. For the investigation of medical images, deep learning has emerged as the preferred methodology. This study provides a thorough examination of the application of deep learning to object detection, segmentation, and classification. It also examines the literature on deep learning-based segmentation and identification techniques for dental images. To identify dental caries, several techniques have been used to date. However, these techniques are inefficient, inaccurate, and unable to handle a sizable amount of datasets. There is a need for a way that can get around these issues since the prior methods failed to do so. In the domains of medicine and radiology, deep convolutional neural networks (CNN) have produced amazing results in predicting and diagnosing diseases. This new field of healthcare research is developing quickly. The current study's objective was to assess the effectiveness of deep CNN algorithms for dental caries detection and diagnosis on radiographic images. The Convolutional Neural Network (CNN) method, which is based on artificial intelligence, is used in this study to introduce hybrid optimal deep learning, which offers superior performance.**

Keywords—Dental caries; deep learning; convolutional neural network

I. Introduction

Detecting dental caries was an exciting task due to the information gleaned from various radiographic images [1]. One of the most frequent chronic illnesses worldwide is dental caries. Especially large, obvious cavities on afflicted teeth respond well to such treatment methods. The effectiveness of conventional approaches has been hindered by the complicated visual features of dental caries images, which include concealed or difficult-to-access lesions [2]. The majority of common caries detection techniques focus on visual examination of the teeth, which also seems to be effective for both big, clearly apparent carious lesions and those that are only faintly visible but may be seen in hand mirrors. Dental radiography is used to find lesions that are hard to see or that are otherwise concealed from view [3]. The adoption of new instruments is advantageous since early diagnosis of dental caries lesions is a key therapeutic factor. The area of health care with the biggest growth is dentistry treatments.

By doing this, the danger, therapy, and identification of oral disorders are reduced [4]. Bitewing radiographs are frequently used by dentists to help them find tooth cavities. They concentrate on both the radiological data and the medical background of their patients. Detecting dental caries is a difficult process, and even skilled dentists may fail to spot carious lesions on bite-wing radiographs [5]. Dental caries detection methods have also typically used visual-tactile methods [6]. Visual-tactile techniques have poor sensitivity, particularly when applied to the surfaces of the proximal posterior teeth. Although radiographic techniques entail the utilization of ionizing radiation, they have a high sensitivity [7]. It might be challenging to detect cavities in certain teeth early on. Numerous carious lesions are discovered at a later stage [8]. The great majority of its screenings, however, are based on data analysis, even though dental radiography is often recognized as one of the most accurate screening methods for finding dental caries. Additionally, there is little research on identifying and diagnosing dental caries [9]. The effectiveness of deep learning techniques for spotting dental cavities in bite-wing radiographs. Blob identification on bite-wing radiographs helps us specify where and how to look for dental caries.

Blob detection is a statistical method for identifying particular regions in radiographic or digital images. Blobs are areas that stand out greatly from their surroundings. Blobs are also areas that contrast with their environment in brightness or darkness. Since their locations are derivative functions, blob detectors fall within the category of variable approaches. Blobs include data about different areas of interest that may be utilized in subsequent image processing with an increase in popularity in the processing of medical imaging [9]. Dentists frequently employ biting radiography to help identify tooth cavities. But this is a challenging procedure. Dentists use their clinical knowledge and the people's clinical background to validate their radiographic caries results. Even seasoned dentists tend to overlook cavities. Dental caries is brought on by an inflammation of the calcified tissue on the teeth. Through early discovery and treatment, they are easily preventable [10].

Effective and prompt treatment may result from the development of a reliable framework for the identification and categorization of dental caries [11]. Cavities are one of the most prevalent illnesses of the mouth that impact individuals of all ages, from infants to elders. It is a condition that weakens the structure of the teeth. Caries is mostly brought on by bacteria that turn the glucose and carbohydrate in food into acid. Because this acid melts and damages the minerals in the enamel, it causes significant damage to the tooth. Dental caries is a chronic condition that most patients experience a delayed onset of. It may impact the dentine tissue, which lies underneath the cementum and enamel on the root, as well as the enamel and cementum's exterior coverings. Infant and toddler caries is the term used to describe cavities in young children's primary teeth [12].

Dental hard tissues undergo periodic demineralization and remineralization as a result of the multifactorial, dynamic, biofilm-mediated illness known as dental caries. Including both permanent and primary teeth, caries can develop at any age and harm the tooth crown as well as the exposed root portions over time. Caries' start and development are impacted by the imbalance of protective and pathogenic factors. The categorization of individuals and groups into carious lesions risks identified is supported by the interplay of these variables, allowing for a more individualized approach to management [13]. Dental caries is a treatable, unequally distributed illness that imposes high costs on both the economy and the quality of life. The worldwide drop in cavities over the past several decades is attributed to the regular utilization of toothpaste. To find caries, experienced testers often conduct a thorough visual examination of clean teeth. Even though they are still frequently utilized, pointed dental probes offer little additional diagnostic value and can harm some teeth.

The detection and treatment of dental caries are changing [14]. Dentists presently use optical, tactical, and radiological data to identify somewhat severe alterations in the oral hard tissues. Instead of treating the illness itself, the clinical therapy of dental caries has focused on treating its symptoms by implanting solutions. Utilizing cutting-edge equipment, dentists would be able to identify developing dental caries before the clinically noticeable white spot. Dental caries is a continuing phenomenon that can be stopped at any stage—from the beginning to the end. When chemicals from bacterial respiration spread into enamel and dentine and break down the mineral, a dental cavity develops as a fungal illness. As a consequence of the bacteria's metabolism of fructose and glucose, organic acids are created [15].

But it has been known for more than a generation that bacteria digest meals produce acids that dissolve tooth minerals and cause dental disease. Dental caries is a contagious bacterial condition mostly brought on by the germs mentioned above feasting on the carbohydrates that people put in their mouths. In the dentistry industry, detecting dental caries is still referred to as the finding of demineralized areas, particularly cavities. Instead of responding medically before cavitation occurs and while the nutrition loss mechanism is still repairable, or at the very least may be implicated, the practising dentist "fixes" cavities by drilling and filling. Dental caries is not the actual disease; rather, it is symptomatic of an existing and past illness. As a result, it is crucial to document the beginning phase of parasite infection or the phases of lesion growth that are not cavitated. [16].

The key contributions of this study are:

- Initially, radiographic images from a large number of patients are collected, and the datasets are analyzed in the framework.
- Moreover, the collected images contain noise, which is filtered using the Wiener filter.
- The filtered images are subjected to segmentation, in which an enhanced Bat Whale optimization model has been used.
- The GLCM is used in the feature extraction to extract the features, and the Convolutional Neural Network is used for classification.
- The BWO-CNN model continues to perform best in terms of accuracy and provides independent advice to the medical professional in the classification of dental images.

The remainder of the essay is divided into the following sections. In Section 2, a summary of prior research on dental caries is provided. Section 3 discusses the proposed classification and framework. Section 4 presents the findings and a discussion of both the proposed and current approaches. The article comes to a close in Section 5 with a few more observations.

II. Related Works

Some of the literature related to dental carries are summarized as follows:

Deep learning for earlier dental caries identification in bitewing radiographs was proposed by Shinae Lee [17]. In this work, they evaluated whether a convolutional neural network model for caries identification on bitewing radiographs employing a U-shaped deep CNN may enhance physicians' effectiveness. The study conformed with all applicable standards of ethics. 304 bitewing radiographs altogether were utilized to train the convolutional neural network model, and 50 radiographs were employed to assess its efficacy. On the entire test dataset, the convolutional neural network model performed pretty accurately in terms of accuracy, recall, and F1-score, with scores of 63.29%, 65.02%, and 64.14 % respectively. The overall classification performance of all three physicians improved significantly when utilizing the convolutional neural network model findings as the data source to identify caries, as seen by an enhanced sensitivity ratio. Thus, physicians may benefit from using the deep learning model to effectively identify dental caries. Despite matter how much the diagnostics performance of the CNN model is improved, there will inevitably be some false-positive mistakes.

Prerna Singh and Priti Sehgal employed the optimal CNN-LSTM for the categorization and preparation of the G.V. Black dental caries [18]. A common health issue for many individuals worldwide is dental caries, a type of oral illness. Inflammation of the calcified tissue of the teeth leads to dental caries. Early detection and treatment make it simple to avoid and cure them. One approach that is well-liked around the globe is the G.V. Black Categorization for dental caries. Depending on the location of caries, it divides the condition into six classifications. To identify and diagnose dental caries on periapical dental images, a novel deep convolution layer network using an LSTM model is proposed in this research. This study's primary goal is to identify dental cavities and categorize them according to the G.V. Black Classification. Deep convolutional neural networks receive pre-processed periapical dental images as input. The Dragonfly optimization technique was used to optimize the suggested algorithm, which provided an accuracy of 96%. Examining and contrasting the suggested model with current state-of-the-art deep learning models is done through experiments. The suggested ideal CNN-LSTM model exhibits the best efficiency and aids in the categorization of dental images as a recommendation for the medical specialist.

The Logit-Based Artificial Bee Colony Optimization Approach was utilized by M. Sornam and M. Prabhakaran to classify dental caries using a back propagation neural network [19]. Caries, a bacterial infection that may cause oral discomfort, is a problem that can greatly reduce people's capacity to carry out their daily activities. Dental practitioners are working hard to discover a suitable strategy to minimize the miscategorization of dental caries phases and probable incorrect diagnoses. Utilizing dental X-ray images as the numerical input produced through a GLCM, a texture feature extraction process, this method is used to strengthen the back-propagation algorithm for an appropriate training and testing process, thus further achieving the best categorization accuracy. But the obtained accuracy is not higher when compared to the other optimization techniques.

For teledentistry, Devesh Saini et al. [20] presented a convolutional neural network for the identification of dental cavities. The primary cause of tooth loss is dental caries, a bacterial illness that progresses over time. This happens as a result of bad dental hygiene, which also causes several dental illnesses. This study attempts to identify dental cavities utilizing digital colour images at a preliminary phase, allowing for simple and efficient treatments. On a categorical collection with caries-containing and non-caries-containing images, training, validation, and testing have been done. Vgg16, Vgg19, Inception v3, and Resnet50 models are employed to attain classification performance, with Inception v3 achieving the greatest efficiency among them with training and validation accuracy of 99.89% and 98.95%, respectively, with the least loss when comparing to Vgg16 CNN models.

Hongbing Yu et al. [21] proposed a new method for Dental Caries Identification on the Child's First Permanent Molar. Recent studies have revealed a significant incidence and prevalence of caries in children's teeth, particularly in the first permanent molar, which might be very harmful to their overall health. Luckily, early identification and prevention can lessen treatment complexity and safeguard kids' dental health. To develop a new method for completely automated identification of dental caries on a child's first permanent molar, they present a unique caries identification and evaluation (UCDA) architecture in this research. The presented UCDA system primarily consists of a backhaul that is started with ResNet-FPN and two simultaneous task-specific subnetworks for area reduction and area categorization. These subnetworks were motivated by an effective in-network featured pyramid and anchor boxes.

Shashikant Patil et al. [22] proposed an algorithm for the detection of dental caries employing an adaptable neural network architecture. AI approaches have a long-lasting effect on biomedicine and provide broadly recognized results. The study's only goal is to examine the effectiveness of combining the Adaptive Dragonfly algorithm, Neural Network classifier, feature extraction, and categorization of dental images for accurately detecting caries. The suggested caries classification method in this case is made to accurately identify dental cavities. The two key stages of this technique are feature extraction and categorization. To assess performance, the 120 entire picture database is divided into three sets at random. Additionally, this classification of the test scenarios helps to guarantee speed improvement. Comparing the proposed MPCA-ADA model to other existing features allows for the model's performance to be assessed. The potential effectiveness of IP and NN algorithms for the identification and treatment of dental caries is emphasized in the study effort.

III. Proposed BWO-based CNN

The radiographic images of dental caries are first gathered. The images are then used for training and testing purposes. Images from dental caries radiography go through a pre-processing stage where the wiener filter is employed to eliminate the extra noise. In this work, dental cavities are detected early on using a combined bat and whale optimization technique. Dental caries and their severity are categorized using the proposed BWO-CNN approach. To operate enormous datasets and obtain a greater accuracy value, a convolutional neural network is used. Fig. 1 represents the various stages of the detection of dental caries.

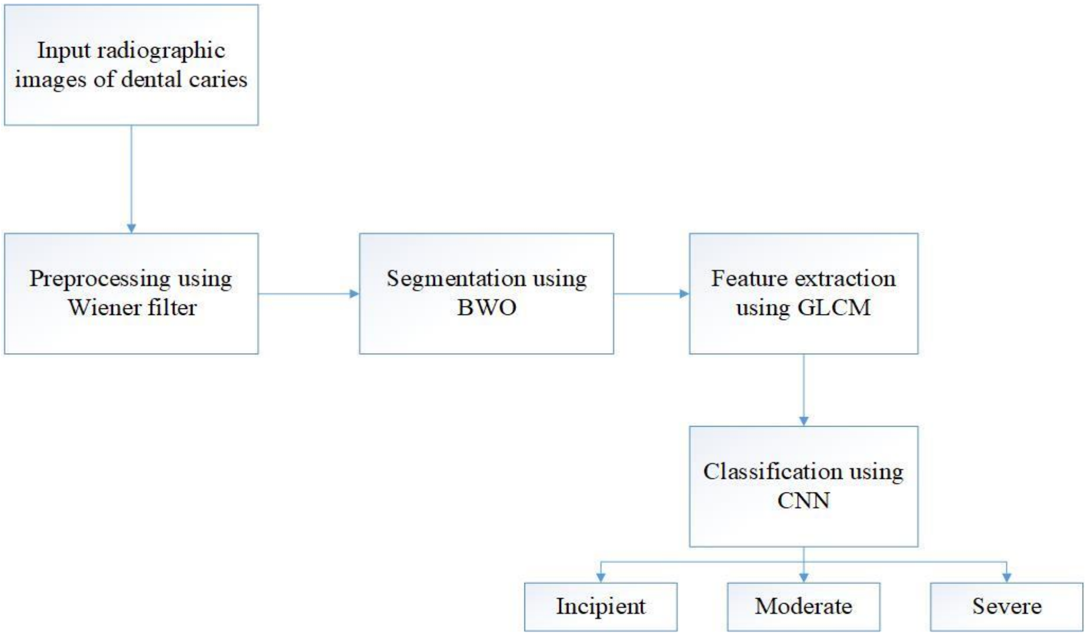

Fig. 1. Proposed BWO-CNN model.

A. Data Collection

This experiment employed data from about 10,000 datasets, including radiographic images of dental cavities. 50 per cent of the images from this set are utilized as training data and 50 per cent are used as testing data. Accordingly, 5000 radiographic images of dental caries are used as training data and 5000 radiographic images of dental caries are used as testing data.

B. Pre-processing

To detect dental caries, pre-processing is the initial step. It is employed to fill in dataset gaps and remove irrelevant data. The radiography images are impacted by independent and abnormal noises, which reduces the sample image analysis rate. The speckle noises, which can be induced by both internal and external sources, have a significant negative impact on radiography images. To minimize the noise in dental caries radiography images, the developed Wiener filter is used. The wiener filter is a linear filter used to conceal visual noise. The BWO-CNN model for identifying dental caries, therefore, makes advantage of the noise-reduced images. Given the wiener function,

$$w(a, b) = \sigma^2[m - p(a, b)] \quad (1)$$

Here σ^2 is the Gaussian noise variance, a and b are the dimensions of the pixel, and m is the feature of noise.

C. Segmentation using BWO

In radiography images, the segmentation procedure is primarily utilized to isolate the afflicted area. The effectiveness of the segmentation process is necessary for the execution of image processing. Image segmentation is frequently used to identify where dental cavities are present as well as any limitations posed by curves and lines in the images. Image segmentation divides the images into sets of pixels and labels the pixels in the samples. The primary objective of image segmentation in medical image processing is to identify dental cavities and produce sufficient data for further identification. Here, an upgraded and optimized Bat and whale algorithm are used to complete the image segmentation.

D. Bat Optimization algorithm

The echolocation of microbats was used to develop a metaheuristic bat algorithm. Bats typically utilize echolocation to find food. The bats typically emit brief pulses, but when they come upon food, both the pulse rate and frequency rise. The precision of the location is improved and the echolocation time is reduced due to the increase in frequencies. Each individual in the bat algorithm has a fixed position $u_i(n)$ and velocity $v_i(n)$in the search space, which are upgraded as the number of iterations rises. The new positions $u_i(n)$ and the velocities $v_i(n)$ can be calculated as follows:

$$u_i(n+1) = u_i(n) + v_i(n) \quad (2)$$

$$v_i(n+1) = v_i(n) + (u_i(n) - q(t)).f_i \quad (3)$$

$$f_i = f_{min} + (f_{max} - f_{min}).\beta \quad (4)$$

Where [0, 1] is the range of the random vector, which has a similar distribution. f min = 0, f max = 1, and q (t) represents the current global optimal solution.

1) *Whale optimization algorithm:* The whale optimization algorithm was inspired by humpback whales' use of bubble nets for hunting. The humpback whales will randomly locate their prey, begin to envelop it in a spiral-shaped bubble, and then swim up toward the surface. Two steps make up the whale Optimization algorithm. The prey is randomly hunted in the first phase, and then spiral bubble nets are used to enclose and attack the prey in the second phase. To find its prey, the whale must be in the best possible posture. The equation shown below can achieve this:

$$\overrightarrow{Y}(i+1) = \vec{Y}^*(i) - \overrightarrow{A} \cdot \vec{B} \quad (5)$$

$$\vec{B} = | \overrightarrow{C} \cdot \vec{Y}^*(i) - \vec{Y}(i)| \quad (6)$$

$$\vec{D} = 2 \cdot \vec{z} \cdot \vec{r} - \vec{z} \quad (7)$$

$$\vec{C} = 2 \cdot \vec{r} \quad (8)$$

The ideal whale posture is represented by $\vec{Y}^*$ *(i)*. The search agent's current location is given by the variables $\vec{Y}(i+1)$ and $\vec{B}$ (the range between the whale and its target). The coefficients are $\overrightarrow{C}$ and $\vec{D}$. The value of z decreases from 2 to 0, reaching 0 at the end of the iteration. A random variable, $\vec{r}$, has a value between 0 and 1.

2) Bat-Whale Optimization algorithm: To reliably identify dental caries, the traits of both whales and bats are merged and optimized. The whale's fitness is indicated in eq. (9)

$$y_i(n+1) = y_i(n) + v_i(n) - \overrightarrow{D} \cdot \vec{B} \quad (9)$$

Algorithm: BWO-CNN mechanism

Input: *Radiographic images of dental caries*

Output: *Detection of regions with dental caries*

Load input images

Train the input images P_i in the system, where i = 1 to n

Pre-processing of images

Let J(i) be the input image from the dataset

$w(a, b) = \sigma^2[m - p(a, b)]$ // Wiener filter

Segmenting the affected part // Bat and Whale Optimization

Initially, the affected part is detected using Eqn. (2)

If (initial region is met)

Update the fitness of Bat and Whale to find the next affected region using Eqn. (9)

Else

Find the initial location

Repeat until the stopping condition is reached // until all the affected region is identified

End if

Return

Feature extraction using GLCM

Classification of dental caries //CNN Classifier

E. Feature Extraction

Inexperienced data are transformed into numerical traits called features that can be used to save the information in the original data set. Each patient perceives images differently; these traits are derived from the total number of images captured. The image's dimensions are enhanced during testing, however, to identify dental cavities, the image's dimensions must be decreased. The processing of feature extraction helps to resolve this issue. In feature extraction, GLCM is used. Correlation, energy, homogeneity, contrast, entropy, and other second-order image attributes are examined to eliminate the probabilistic texture feature.

1) Energy: Squares with frequently higher grayscale values and unpredictable concentration values in images are summed to create energy. In Eq. (10), the energy of the input data is determined.

$$E = \sum_x \sum_y \{N(x, y)\}^2 \quad (10)$$

Where the squares in the image with grey levels are labelled as (x, y), and the images are denoted as N.

2) Contrast: The local contrast of an image is measured using features, and it is projected to be low when the mean concentration is even. The complete grayscale information of the main image is then projected, as per Eq. (11),

$$C = \sum_{a=0}^{I_y} a^2 \left\{ \sum_{x=1}^{I_y} \sum_{y=1}^{I_y} M(x, y) \right\} \quad (11)$$

(x, y) represents the square of an image's grayscale, N represents the images, and *I* stands for the images' grayscale.

3) Correlation: Using the correlation characteristics shown in Eq. (12) the numerical connections between the variables and the proportional dependency of grey levels on pixels.

$$C_o = \frac{\sum_x \sum_y (x, y) N(x, y) - \mu_u \mu_v}{\sigma_u \sigma_v} \quad (12)$$

The values of the mean and standard deviation in the images are represented as rows and columns by the letters μ_u, μ_v, $\sigma_{u,}$ *and* σ_v.

4) Entropy: Entropy is referred to in Eqn. (13), the anticipated high value of the range of grey levels being randomly generated sticks out.

$$En = -\sum_x \sum_y N(x, y) \log(N(x, y)) \quad (13)$$

F. Classification using Convolutional Neural Network (CNN)

To identify dental caries, CNN classifiers are used. It effectively evaluates the radiography images and extracts the necessary characteristics. Four layers are present in convolutional neural network classifiers: the convolutional layer, the max pooling layer, the fully connected layer, and the softmax layer. The CNN ranges the intensity values of the image pixel before the training phase. CNN is the model that trains the quickest. The input radiography image ought to be the same size. Each image in the training set has an equation that is presented in Eq. (14).

$$p(a, b) = \frac{o(a,b) - \mu}{\sigma} \quad (14)$$

1) Convolutional layer: A convolution layer was used to decrease the image of factors and extract the important features. The convolution layer includes rotation invariance, scaling partially invariant, and interpretation invariance. Both the over-fitting problem is lessened and the generalization idea is added to the fundamental framework. The convolutional layer collects a variety of images to analyze how complicated each one is. It is related to the qualities we seek in the given image. It is written as an eqn. (15).

$$f_i^m = x(\sum_{j \in M_i} f_j^{m-1} * p_{ji}^m + x_i^m) \qquad (15)$$

M_i – It stands for an input choice. The output has been specified as an additive bias b. When the sum of maps a and b across map i the kernel is applied to map i.

2) Max pooling layer: In order to reduce fitting and the size of the neurons used in the downsampling layer, this layer is used. The pooling layer reduces the rate of calculation, the size of the feature map, the training time, and regulates overfitting. Overfitting is calculated using an equation and is defined as 50% on test data and 100% on the training dataset.

$$x_{mab} = max_{(s,t) \in} f_{mst} \qquad (16)$$

Map, f_{mst} is the component at (s, t) in the pooling region pst, and it represents the immediate area.

3) Fully connected layer: In the field of classifying images, a Fully Connected Layer has been applied. The FC layers are placed after the Convolutional layers. The FC layer makes it easier to map a picture between the input and output. Fully linked layers make up the network's upper tiers. The output of the max pooling layer serves as the input for the fully connected layer.

4) Softmax layer: The Softmax layer converts the values into a normalized ratio distribution. The output is provided to the classifier as an input. The dental caries structure is implemented in the Softmax layer and the Softmax classifier is the standard contribution classifier. It is depicted in Eq. (17).

$$\sigma(\vec{X})_n = \frac{e^{x_n}}{\sum_{i=1}^{n} e^{x_i}} \qquad (17)$$

The whole process for detecting dental caries is shown in Fig. 2. The loading of input images starts the flowchart. The next step after loading the images is to train the loaded images. The Wiener filter is used during pre-processing to get rid of any unwanted noises from each image. The segmentation method uses the images that have had the noise removed. The segmentation process uses the suggested BWO-CNN. Using Eq. (2), the impacted region's position is initially determined. If the first region is met, use equation (9) to locate the subsequently impacted region; otherwise, return to the previous step and repeat the calculation of equation (2) until the initial region is fulfilled. Repeat Eq. (9) after identifying the subsequently impacted region until the stopping condition is satisfied. The process moves on to feature extraction if the halting condition is satisfied. GLCM is used for feature extraction. Following that, a Convolutional Neural Network is used to classify dental caries.

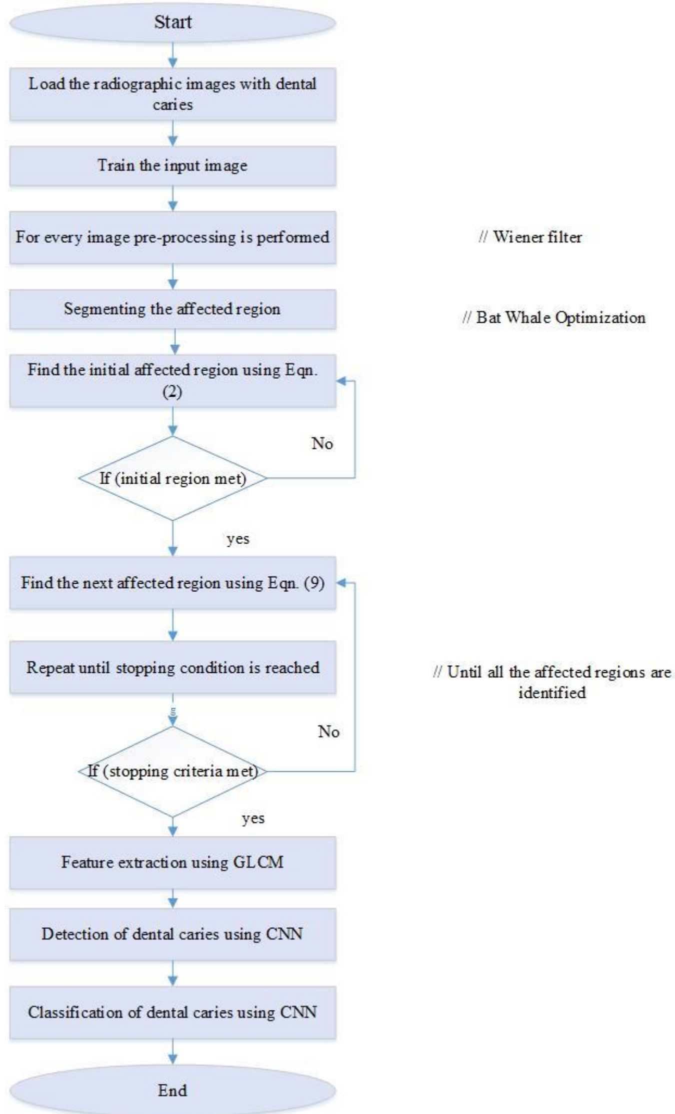

Fig. 2. Flow diagram of the BWO-CNN model.

IV. Results and Discussion

The existing methods consume a large time for processing and they cannot process a large number of data sets. More precise accuracy cannot be achieved with the existing methods. The employed BWO-CNN method overcame these limitations. The proposed strategy has been tested utilizing dental caries radiography datasets. The combined innovative bat and whale optimization-based convolutional neural network is employed to identify dental caries. Performance metrics are used to evaluate how well the given approach is presented.

A. Accuracy

Measured by accuracy, the system model's performance across all classes is evaluated. In general, it is the idea that all observations will be correctly predicted. In Eq. (18), accuracy is expressed.

$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \quad (18)$$

B. Precision

The number of correct positive assessments that deviate from the overall positive evaluations is used to measure precision. By using an Eq. (19), you can compute the precise identification of dental caries,

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \quad (19)$$

C. Recall

The relationship between the number of genuine positives correctly labelled as positives and the overall number of positive samples is known as the recall. It describes the proportion of predictions that were correct in the Eq. (20) based detection of dental caries,

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \quad (20)$$

D. F1-Score

The F1-Score calculation is the combination of recall and precision. The F1-Score shown in Eq. (21) is calculated using precision and recall.

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \quad (21)$$

Table I shows that the training accuracy of CNN and BWO-CNN is 99.2% and 99.55% respectively. The testing accuracy of CNN and BWO-CNN is 97.3% and 98.6% respectively. It is represented in Fig. 3.

TABLE I. PERFORMANCE EVALUATION BASED ON BWO-CNN

	CNN (%)	BWO-CNN (%)
Training accuracy	99.2	99.5
Testing accuracy	97.3	98.6

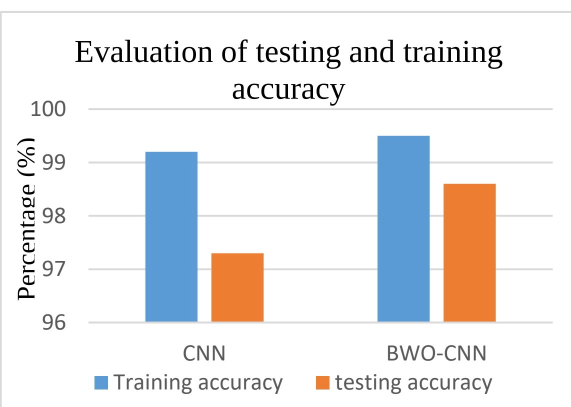

Fig. 3. Evaluation of testing and training accuracy.

TABLE II. ACCURACY COMPARISON OF VARIOUS METHODS

Method	Accuracy (%)
U-shaped deep CNN	63.29
CNN-LSTM	96
CNN	98.95
BWO-CNN	99.12

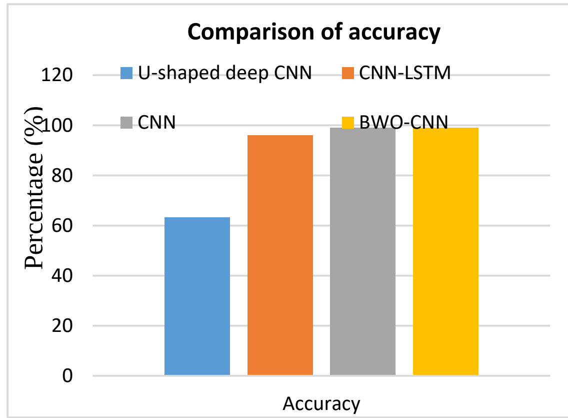

Fig. 4. Comparison of accuracy.

The projected technique Combined novel Bat and Whale Optimization-based Convolutional Neural Network achieves higher accuracy when compared to the existing dental caries detecting methods such as U-shapes CNN, CNN-LSTM, CNN, and BWO-CNN which are tabularized in Table II. Fig. 4 represents the Comparison of accuracy between BWO-CNN and other methods.

The projected technique Combined novel Bat and Whale Optimization-based Convolutional Neural Network achieves higher recall when compared to the existing dental caries detecting method like U-shaped CNN and BWO-CNN which are tabularized in Table III. Fig. 5 represents the Comparison of recall between BWO-CNN and U-shaped CNN.

TABLE III. COMPARISON OF RECALL

Method	Recall (%)
U-shaped deep CNN	65.02
BWO-CNN	92

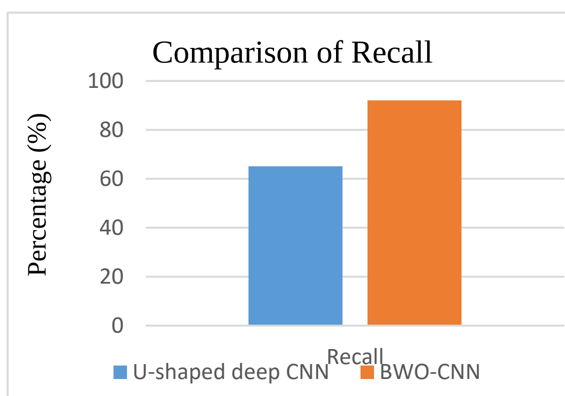

Fig. 5. Comparison of recall.

TABLE IV. COMPARISON OF F1-SCORE

Method	F1-score (%)
U-shaped deep CNN	64.14
BWO-CNN	91

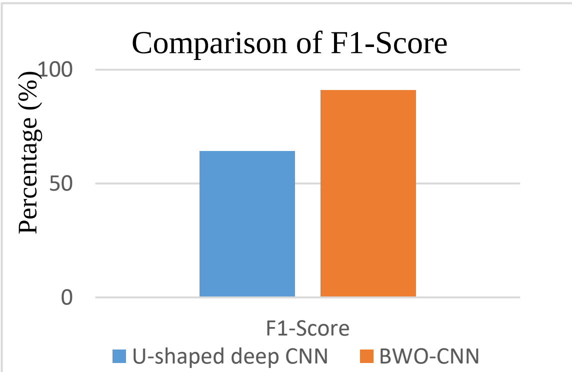

Fig. 6. Comparison of F1-score.

The proposed technique Combined novel Bat and Whale Optimization-based Convolutional Neural Network achieves a higher F1-score when compared to the existing dental caries detecting method like U-shaped CNN and BWO-CNN which are tabularized in Table IV. Fig. 6 represents the Comparison of recall between BWO-CNN and U-shaped CNN.

V. CONCLUSION

Although image processing in medical technology is expanding quickly nowadays, there are some situations where the complexity of the images makes it challenging to classify and identify diseases. The suggested approach is utilized to categorize, find, and segment the diseased or damaged portion. It focuses mostly on finding dental cavities. Individuals' information is first provided through radiographic images of patients with various types of dental caries, which are gathered. The unwanted effects or noise in the radiography images are then eliminated during the pre-processing step using a wiener filter. GLCM was used for feature extraction. Additionally, the damaged part is segmented using the suggested BWO-CNN method, and dental caries is classified using a CNN. Using BWO-CNN, high categorization and accuracy are also attained. The prediction accuracy of this model was 99.12% as a consequence. Even though the proposed method is effective, the performance can be increased by introducing LSTM. Therefore, in the future, a lot of research is being focused on creating a lightweight CNN-LSTM model that can shorten training time and is resistant to weight initiation effects.

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