Longevity Prediction of Root Canal Treatment using CNN-Logistic regression model

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Abstract:
The root canal treatment can provide long-term relief and preserve the tooth. In general, root canal treatment has a high success rate and can last for many years, often preserving the tooth for a lifetime. However, it should be noted that no dental treatment can guarantee a permanent solution. The longevity of root canal treatment might vary depending on several factors, including the clinical and non-clinical factors such as overall health of the tooth, the quality of the treatment performed, and the oral hygiene practices of the patient along with overfilling, under filling, perforation, or root Resorption.

Therefore, the purpose of this research is to forecast how long a root canal treatment will remain by identifying the factors that are responsible for the treatment failure. The system makes the use of textual and image dataset along with logistic regression and CNN in order to find the non-clinical and clinical factors which can more likely to result in treatment failure. Moreover, the fusion of logistic regression and CNN also help to predict the longevity of the treatment with the higher accuracy of 94.16%.
Keywords: Root Canal Treatment Failure, Toot Longevity Prediction, Overfilling, Under Filling, Perforation, Root Resorption, Deep Learning, CNN, Logistic Regression, Fusion Approach.
DOI: 10.24297/j.cims.2023.6.11v

1. Introduction

Longevity is an essential factor to consider when predicting the outcome of root canal treatment (RCT) [1]. Endodontic treatment, commonly known as root canal therapy, is a process used to repair infected or injured dental pulp within the roots of a tooth. This treatment helps to remove infection, relieve pain, and restore the tooth's functionality. Thus while predicting the success of root canal treatment, longevity refers to the ability of the treated tooth to remain functional and symptom-free over an extended period of time [2]. Thus long-term success of RCT is depend on different clinical and non-clinical factors [7].

Moreover, root canal treatment longevity, is the survival of teeth following RCT. According to an article published in the Journal of Dental Research on the longevity of teeth following root canal therapy, by examining the data from 46,000 patients who underwent RCT, teeth may survive for approximately 11 years after a root canal. It has also been observed that if the tooth received orthodontic treatment, such as a filling and crown following a root canal, the tooth's longevity increased to 20 years. [3]. According to several studies, when the highest standards are upheld throughout the procedure, root canal success rates range from 90–95 % [4].

As neither orthodontic treatment can guarantee a long-lasting solution, the causes of treatment failure cannot be ignored. There are various factors can affect the longevity of teeth treated with a root canal, including follow-up treatments such as includes overfilling filling of the canal [5] [11] [13], root fractures, damaged teeth, overfilling [5], pulp stones, and leakage [5] 'Root Resportion [6] or poor dental hygiene [4], age [4][9], smoking, alcohol consumption, geographical location, and lack of formal education are also can lead to treatment failure. Therefore, it is important to find the cause behind the treatment failure to predict longevity. The usage of machine learning [9] and deep learning [10] technique for endodontic treatment has turn out to be more effective way for accurate and efficient diagnoses, with the use of x ray images, thus reducing dentists' workload.

For this, Mohamed et al. [2] made efforts to find dental age estimation utilising machine learning algorithms and deep learning methodologies. The author employed CNN for determining dental age using radiographic data such X-ray images, 3D cone beam computed tomography (CBCT), , and orthopantomography (OPG). Deep learning algorithms such as VGGNet16, the Inception model, EfficientNet, the Xception model, and MobileNetV1/V2 perform well when determining dental age. It will be easier to identify the pattern of the treatment if the cause of the failure can be identified. As a result, Jeon et al. [10] developed a system for root canal treatment failure prediction from panoramic radiographs using CNN approach. As these C-shaped canals present challenges for canal enlargement, irrigation, and obscuration, root canal treatment failure rates are high in teeth with such canals. The study used data from 1020 patients in total, with a 95.1% accuracy rate.

This paper made an attempt to find the different causes such as clinical cause and non-clinical cause of Root canal treatment failure [14]. In order to find clinical cause of the failure CNN has been used on image dataset of 379 Images. The system can classify image sin to six classes such as 'Ideal RCT', 'Instrument breakage', 'Overfilling', 'Perforation', 'Root Resorption', 'Under filling' [13]. In order to find the nonclinical reason for treatment failure the use of Logistic Regression has given prominent accuracy. The Dataset of 332 instances has been used for the experimentation to determine possible causes of treatment failure. Again to predict the longevity of the RCT treatment, the fusion approach of CNN + LR has been used.

2. Proposed System

Considering the importance of longevity in the prediction of root canal treatment, it helps dentists and patients make informed decisions regarding treatment options and allows for the best possible outcomes in terms of function, comfort, and oral health. The suggested strategy would can assist in determining clinical and non-clinical aspects that can cause the treatment failure by making the use of CNN and Logistics regression respectively as shown in system architecture (Refer figure 1). Additionally, the system also helps to find the longevity of the RCT for people who have had root canals.

Dataset collection:

The given system can able to detect the clinical and non-clinical causes that can cause root canal treatment failure using root canal image dataset of total 379 images as well as text dataset having overall 332 instances of root canal therapy. The relevant data has been collected through collaboration with dental professionals and extensive research in order to construct a machine learning and deep learning model for failure detection.

Data pre-processing:

There is a lot of noise in the text data. It is pre-processed to provide refined data by utilising noise removal methods or preventing any other data disturbances. Furthermore, colour, orientation pre-processing is employed to improve dental image quality in addition to contrast augmentation, so that more clear images are retrieved to provide effective output. The dental x-ray images had been cropped and reduced to 224 *224 pixels before training.

Model Building:

Building Logistic Regression(LR) Model

The machine learning approach used here is help to find out the non-clinical cause of root canal treatment failure. Once the features extracted and normalized the Logistic Regression, model has been trained on 332 instances dataset. Here for training we have used 90% instances of the total dataset and remaining 10% are used for testing. Thus after training the model and comparing it against the testing dataset, system classified the data in two main categories such as high-class attributes (those that have a lower risk of failing) and low-class attributes (those that are less likely to result in failure). Thus this technique helps to find out the most non clinical factors such as age, poor oral hygiene, chewing habits, eating habits, uncooperative behaviour, bad habits, demographic area, education of patient which are mostly responsible for root canal treatment failure.

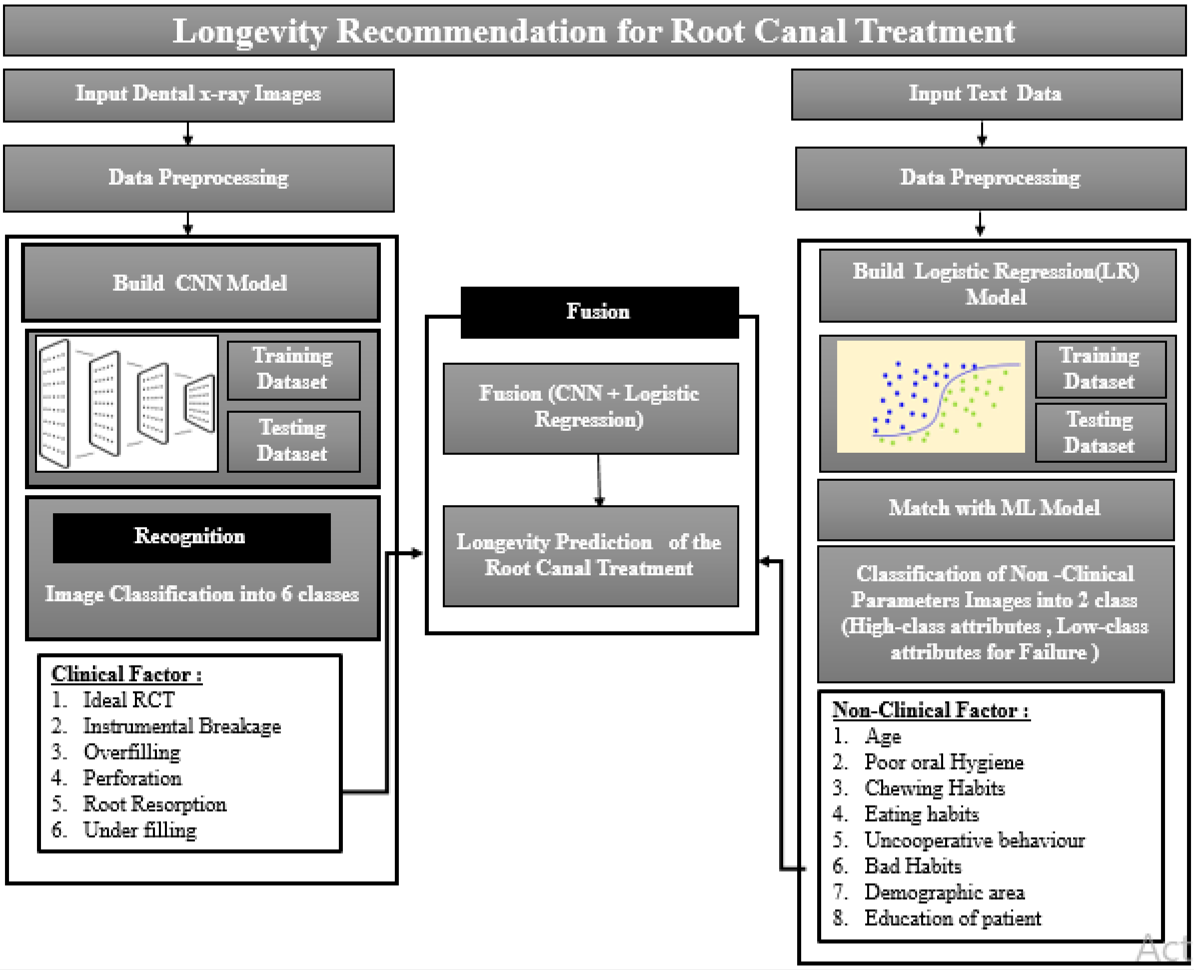

Figure 1: System Architecture

Building CNN Model

Deep learning model has been used to recognise the clinical cause of RCT failure with the use of 379 dental x-ray images. Thus the CNN model is trained, by using 60% of images of each class (Ideal RCT – 96 images, 'Instrument breakage' -63 images, 'Overfilling -44 images, Perforation – 88 images, Root Resportion 36 images, and Under filling -52 images). Thus after providing an input image to the system, Convolutional layers, pooling layers, fully linked layers, and normalisation layers make up the CNN model that assists in extracting the crucial information from test images. So, the system can recognise the test images belong to the class among the six classes such as 'Ideal RCT', 'Instrument breakage', 'Overfilling', 'Perforation', 'Root Resportion', 'Under filling'. So the model helps to find the clinical cause of treatment failure [13]. The 16 convolutional layers, a pooling layer, and three fully linked layers that make up this CNN are all constructed with a kernel size of 3×3 pixels. The Max pooling layer was created with 2×2 pixel strides.

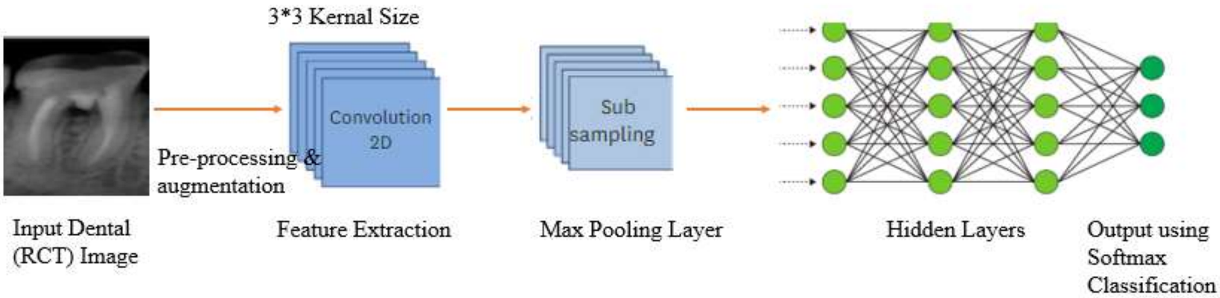

Figure 2: CNN Working

The hidden layer is then utilised to learn and calculate more complicated tasks in order to provide great results. Finally, the image is classified into the six output classes mentioned below using the softmax function. As a result, these layers are used to identify meaningful data such as if there is instrument breakage, overfilling, perforation, root resorption and under filling from an input image.

1. Ideal RCT
2. Instrumental Breakage
3. Overfilling
4. Perforation
5. Root Resorption
6. Under filling

Longevity Prediction with fusion approach:

After identifying the clinical and non-clinical cause of the RCT failure and considering the importance of longevity in the prediction of root canal treatment, the proposed system is able to predict the lifespan of the RCT with the use of Logistic regression and CNN fusion approach.

3. Results and Discussion

Evaluation of Logistic Regression Model

We analysed the machine learning model's effectiveness i.e Logistic Regression on the text dataset of 332 samples related to RCT to find out the non-clinical factors responsible for root canal treatment failure. The given technique has classified the factors into two classes such as

- Class 0 – Low class - features that are mostly expected to lead to failure
- Class 1 – High Class - features that are less expected to lead to failure

In order to assess the efficacy of the machine learning classification, we have calculated accuracy, sensitivity, specificity, and precision. Thus in order to calculate the above parameters classification report has been generated using WEKA (Waikato Environment for Knowledge Analysis) tool. Initially we have uploaded the dataset to WEKA tool and run the Logistic Regression classification algorithm. Thus the classification report that has been generated is as follows:

Table I: Classification Report

Class	0	1
0	203	15
1	14	100

The classification report assists in the calculation of true positive (TP), true negative (TN), false positive (FP), and false negative values, Where,

1. TP: The values that are considered to be positive.
2. TN: The values where Negative models classified as negative.
3. FP: It is the value of items that have been incorrectly labelled as belonging to the class.
4. FN: It is the value where the things that ought to have been classified as belonging to the positive class but weren't

Table II:TP, TN, FP and FN Values

	TP	TN	FP	FN
Class 0	203	100	14	15
Class 1	100	203	15	14

The confusion matrix is generated using the aforementioned data, as shown in table III. Thus the accuracy calculated by below formulas helps in calculating the system's success rate using the calculations below.

Accuracy = TP+ TN/ TP+ TN+ FP+ FN

Precision=TP / (TP + FP)

Sensitivity = TP / (TP + FN)

Specificity = TN / (FP + TN)

Table III: Confusion Matrix

	Accuracy	Precision	Sensitivity	Specificity
Class 0	91.27%	93.55%	93.12%	87.72%
Class 1	91.27%	86.96%	87.72%	93.12%

The present study found that the logistic regression algorithm had higher classification accuracy for identifying the non-clinical parameter for root canal treatment failure. The accuracy, precision sensitivity, and specificity, of the logistic regression model were 91.27%,93.55%,93.12% and 87.72% for class 0 and 91.27%,86.96%,87.72% and 93.12% for class 1respectively (table III). It has been also observed that LR shows same accuracy for both the class 0 and class 1.

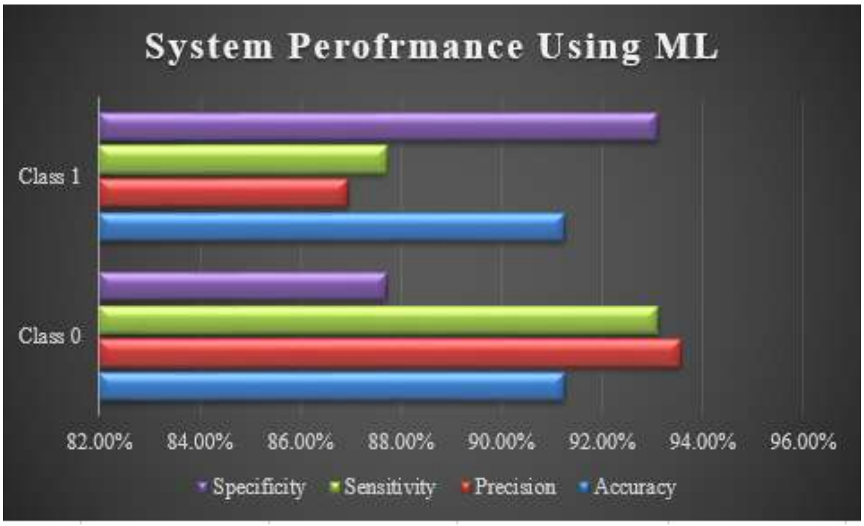

Figure 3: System Performance using Machine learning approach

Evaluation of CNN Model

The experiments are conducted on an image dataset of 339 images are used detect cause clinical cause of the root canal treatment failure, using Convolutional Neural Network (CNN). in terms of image distribution each class has different image count such as (Ideal RCT – 96 images, 'Instrument breakage' -63 images, 'Overfilling -44 images, Perforation – 88 images, Root

Resportion 36 images, and Under filling -52 images). The following figure shows the image distribution of each class.

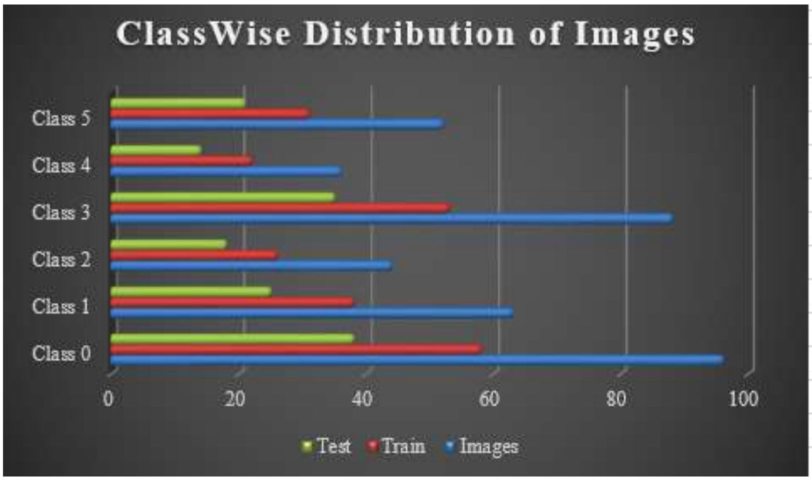

Figure 4: Class wise Image Distribution

As a result, the algorithm divides the image into 6 categories using CNN, including:

- Class 0 = 'Ideal RCT'
- Class 1 = Instrument breakage'
- Class 2 = 'Overfilling'
- Class 3 = 'Perforation'
- Class 4 = 'Root Resportion
- Class 5 = 'Under filling'

The classification report for the above mention classes are as follows:

Table IV: Classification Report

Classes	**0**	**1**	**2**	**3**	**4**	**5**
0	33	0	0	1	2	1
1	0	23	1	1	1	1
2	2	0	16	3	0	0
3	1	2	1	31	0	2
4	2	1	0	0	12	1
5	1	0	0	0	0	16

Based on these classification reports, the true positive (TP), true negative (TN), false positive (FP), and false negative values are calculated. The system performance has been calculated with formulas mentioned above.

Table V: Confusion Matrix

Class	Accuracy	Precision	Sensitivity	Specificity
Class 0	92.91	84.62	89.19	94.23
Class 1	94.93	88.46	85.19	97.3
Class 2	94.93	88.89	76.19	98.29
Class 3	92.25	86.11	83.7	95.24
Class 4	94.93	80	75	97.54
Class 5	95.62	76.19	94.12	95.83

The accuracy, precision, sensitivity, and specificity of the above-mentioned terms from the table are represented graphically in the graph below. It has also been noted that among the 6 classes the class 1,2 and 4 gives higher accuracy in predicting the non-clinical cause of RCT failure. Moreover, it could be pointed out that the system gives the accuracy of 94.16% in detection of RCT treatment failure and its Clinical Factors causes such as Instrument breakage', 'Overfilling', 'Perforation', 'Root Resorption', 'Under filling.

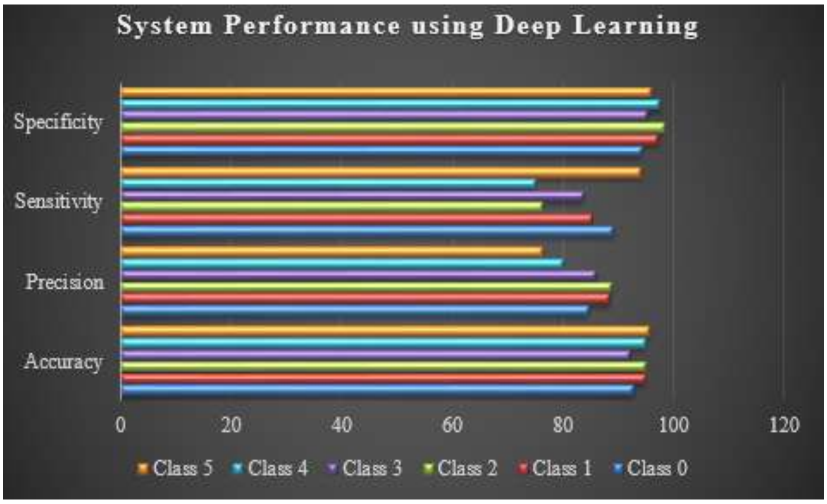

Figure 5: System performance using Deep Learning

Fusion Approach Logistic Regression and CNN for Longevity Detection:

The combination of logistic regression and Convolutional Neural Networks (CNNs) aids in the prediction of tooth lifetime by integrating the strengths of both models. To estimate the duration of the RCT, each image in CNN comprises essential information such as instrument breakage, overfilling, under filling, etc.

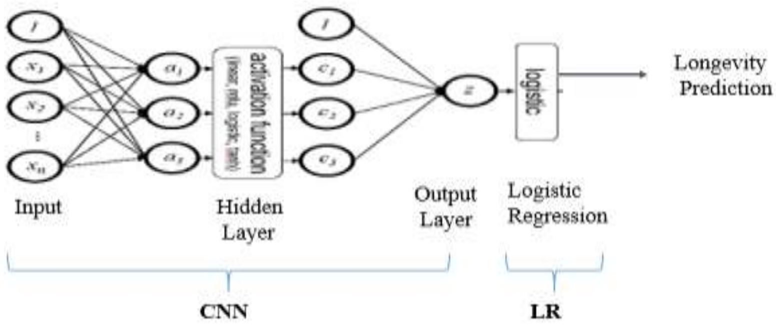

Figure 6: Fusion Approach

Thus, the fusion model can use both visual qualities and extra aspects that contribute to tooth lifetime by merging the visual information obtained by the CNN with other relevant data via logistic regression. Thus it could be pointed out that, it the treatment fails due to the factors such as under filled canals, habits, broken instruments, Overfilled canals, perforation, could affects longevity of the treatment.

4. Conclusion

It's important to remember that while root canal treatment has a high success rate, there can be cases where the treatment fails. Thus this paper sheds a light on the clinical and non-clinical factors that can contributed to the RCT failure. The findings suggest that the integration of visual information extracted from dental images through CNNs, which gives the accuracy of 94.16% in detecting clinical parameters responsible for prediction for root canal treatments. In addition, the use of logistic regression also proven to be effective as it gives the accuracy of 91.27%, in detecting non clinical cause of treatment failure. Additionally, this fusion strategy improves the model's predictive capability, making it possible to anticipate treatment outcomes with accuracy. This fusion model has the potential to help dental practitioners make evidence-based decisions about treatment strategies and prognosis, resulting in better patient care. It should be noted that additional study and validation on larger and more diverse datasets are required to generalise the findings and ensure the robustness of the suggested fusion model.

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