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Detection of Pulpitis Using MFCC and CNN1D

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Abstract. In this paper, we present a crucial problem the public faces in maintaining dental health, specifically related to pulpitis. Pulpitis is an inflammation of the dental pulp tissue caused by various factors such as bacterial infection, trauma to the tooth, or tooth decay. We responded to this challenge by creating an innovative solution to detect and distinguish pulpitis from healthy teeth. This solution will help dental professionals diagnose and treat pulpitis more effectively. The method we applied in this research is pulpitis detection using audio signals with machine learning algorithms. In this study, we used a CNN1D model with the addition of MFCC as a feature extraction with the hyperparameters Adam optimizer, learning rate 0.001, batch size 32, and test size 0.2. The model evaluation used a confusion matrix to assess the model's ability to predict based on sound. Implementing machine learning in pulpitis detection through audio signals can help health workers accurately diagnose the condition.

1 Introduction

Teeth are one of the mouth's accessories, with varied structures and many functions [1]. Ideally, teeth tear and chew food. They also play a role in the digestive process and help speak and express oneself. Teeth have a complex structure consisting of the corona (outer part), ring, and root (inner part). Teeth also have many other functions, such as helping to express emotions and speech and swallowing food [2].

The pulp is the connective tissue within the tooth and has several vital functions [3]. The pulp consists of various tissue components such as intercellular substances, tissue fluid, specific cells, lymphatics, blood vessels, nerves, odontoblasts, fibroblasts, and other cellular components [4]. Embryologically, pulp tissue is formed from the dental papilla's central cells, resembling dentin tissue.

Pulpitis is an inflammation of the teeth pulp, which may cause pain [5]. The pulp is the innermost part of the tooth that contains blood vessels and nerves. There are two types of pulpitis: irreversible pulpitis and reversible pulpitis. Reversible pulpitis is inflammation of the pulp that can heal if the cause is removed. Irreversible pulpitis is inflammation of the pulp caused by a bacterial invasion that has spread so that the pulp tissue defense system cannot repair and cannot recover [6]. Pulpitis can occur due to a variety of factors, including untreated dental caries, trauma, and improper restorations. Root canal treatment (PSA) is one of the endodontic treatments used to treat irreversible pulpitis [7].

In previous research, pulpitis detection has been developed through machine learning with speech signal datasets, which used LPC (Linear Predictive Coding) as feature extraction and KNN (K-Nearest Neighbor) [8]. However, this research has limitations: the dataset is a person's speech with a considerable bias. For example, the voice between men and women is certainly different, and between children and adults is also different.

According to previous research, further research is needed related to pulpitis detection. In this case, we conducted research using the sound of knocking teeth. All human teeth have the same knocking sound in our hearing as humans, but that does not necessarily happen if we apply it to machine learning. Our research aims to detect pulpitis with an accuracy above 75% using MFCC and CNN1D.

2 Methodology

This methodology is divided into four sections: Mel Frequency Cepstral Coefficient, Convolutional Neural Network 1D, dataset creation, training model, and model evaluation.

2.1 Mel Frequency Cepstral Coefficient (MFCC)

Mel Frequency Cepstral Coefficient (MFCC) is a technique for extracting audio features in speech technology and speech recognition. MFCC converts sound characteristics into coefficients that can represent the sound characteristics. MFCC is according to the sense of hearing in humans. This method adopts the principle of the human sense of hearing by filtering logarithmically at frequencies over 1000 Hz and linearly at frequencies below 1000 Hz. This is because

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humans cannot hear sounds with frequencies greater than 1 KHz well [9]. In this study, we used MFCC as feature extraction because of its ability to do well in audio processing.

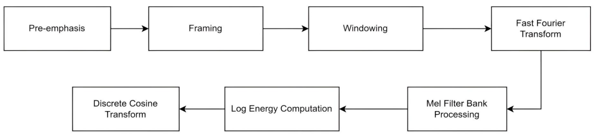

Figure 1. Illustration of how MFCC works

Based on Figure 1, we can see how MFCC works. Pre-emphasis: The audio signal is amplified at high frequencies to improve the quality of spectrum analysis. Framing: The audio signal is split into short frames for more detailed analysis. Windowing: Each frame is multiplied by a Hamming window to reduce the effect of spectrum leakage. In Fast Fourier Transform (FFT), the frames are transformed from the time domain to the frequency domain to obtain the frequency spectrum.

Mel Filter Bank: The frequency spectrum is passed through a Mel filter bank to mimic how the human ear hears frequencies. The logarithm of Power Spectrum: The power spectrum at each Mel filter is calculated and then converted into a log-power spectrum. Discrete Cosine Transform (DCT): The log-power spectrum is applied to DCT to produce more concise and relevant MFCC coefficients.

2.2 Convolutional Neural Network 1D (CNN1D)

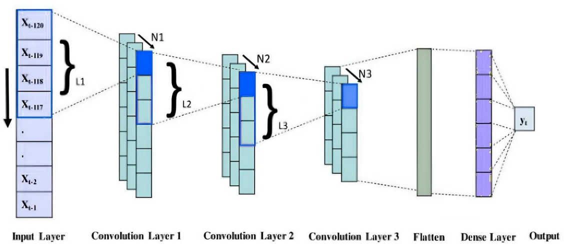

Figure 2. Architecture of CNN1D

1D Convolutional Neural Network (Conv1D) is a very effective architecture for processing sequential data such as audio signals [10]. Based on Figure 2. the input data in audio signals is received by the input layer. Next, the data is processed by several Conv1D layers, each with a specific size filter. The function of the Conv1D layer is to extract local features from the sequential data, which helps detect essential patterns in the audio signal. The first layer, Convolution Layer 1, applies filters to generate feature maps after each convolution layer, which are then further processed by the following convolution layer, Convolution Layer 2, to extract more complex features.

After passing through the convolution layer, the flattened layer processes the data into a one-dimensional vector form to prepare it for entry into the dense layer. Based on the features extracted by the previous convolution layer, the dense layer serves as the final decision-maker. In the final stage, the output layer generates probabilities for each target class.

2.3 Dataset Creation

In this study, we used a dataset of tooth-tapping sounds. The teeth that are knocked are teeth that have pulpitis and healthy teeth. Of course, dental medical experts have validated the tooth-tapping process. All data is packaged in the form of wav files. The total dataset obtained is 180, consisting of 90 teeth that have pulpitis and 90 healthy teeth. Then, the augmentation process is carried out to multiply the data so that later, it can increase the accuracy of the model [11]. After the initial data is augmented, the number becomes 900, then separated into two sections with the following information of training data and validation data: training Data, 80% of the dataset (820 file.wav), and validation Data, 20% of the dataset (180 file.wav). The pure CNN model without MFCC divides the dataset using the following division: training Data 60% of the dataset (540 file.wav) and validation Data = 40% of the dataset (360 file.wav).

2.4 Training Model

We need to perform various steps in model training to achieve the best model. The stages are preprocessing, feature extraction, and hyperparameter.

2.4.1 Preprocessing

The preprocessing stage is the initial stage before entering the algorithm to be used. Preprocessing is a stage to eliminate several problems that can interfere with data processing. For the data to be more structured, preprocessing goes through several stages, namely the Gaussian filter and data augmentation. Gaussian Filter is one of the linear spatial filters that work by correlating the matrix/kernel. This method was chosen because it has a kernel center and is very good for removing normal distribution noise often found in digitized audio [12]. Data Augmentation is a technique used to augment processed data by statistically modifying the data. This technique differs from data synthesis, artificially created without the original dataset [13]. Data augmentation is proper when limited data is available, and you want to improve model performance, increase robustness, and improve data quality.

2.4.2 Feature Extraction

Feature extraction is vital in audio signal processing, especially speech recognition and classification applications [14]. MFCC is an essential step in this process. With more meaningful and efficient feature representation, machine learning models can achieve better and more stable performance in various speech recognition and audio classification applications. Research shows that combining MFCC with modeling techniques such as Conv1D can significantly improve model accuracy and efficiency.

2.4.3 Hyperparameter

Hyperparameter testing is a process that selects the best hyperparameters for model performance. This

system method uses hyperparameter testing, namely optimizer, learning rate, epoch, and batch size, by comparing the best model performance. Therefore, the prepared dataset will be trained using MFCC and CNN1D algorithms with the following hyperparameters:

- Size of Batch = 32
- Rate of Learning = 0.001
- Epoch = 300
- Optimizer = Adam

Apart from the above models, we also looked for the best model for this study. Therefore, we also tested a pure CNN model without additional feature extraction with the following hyperparameters:

- Size of Batch = 8
- Rate of Learning = 0.001
- Epoch = 300
- Optimizer = Adam

Let us look at the difference in batch size and test size. This is because we did repeated experiments for trial and error on hyperparameter tuning, and the model got the most balanced accuracy and loss with the best settings for those numbers. Both models are still relevant for comparison since they use the same dataset for training and validation.

2.5 Model Evaluation

Model evaluation is the stage where the model is evaluated for its performance based on several methods. The methods include using a confusion matrix, which can then be used to determine the F1 score, recall, and precision. Confusion matrix is a standard measurement tool for measuring prediction accuracy in classification systems [15]. The confusion matrix is formed from four pieces of information, namely False Positive (FP), True Positive (TP), False Negative (FN), and True Negative (TN). The four elements of the categorization result in the confusion matrix are shown in the following figure.

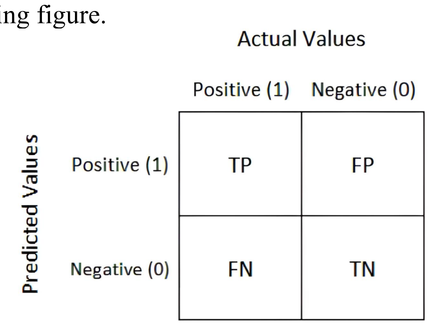

Figure 3. Illustration of Confusion Matrix

Based on figure 3. compares the predicted values with the actual values of the data, with four main terms representing the results of the classification process.

- True Positive (TP): The amount of data classified into the correct class.
- True Negative (TN): The amount of data completely unclassified into the wrong class.
- False Positive (FP): The amount of data incorrectly classified into the wrong class.
- False Negative (FN): The amount of data completely unclassified into the correct class.

According to the confusion matrix, we can compute the f1-score, precision, accuracy, and recall based on the confusion matrix. The ratio of accurate predictions, both positive and negative, to the total data is known as accuracy. The precision measure is the ratio of correctly predicted positive outcomes to the number of optimistic forecasts. The ratio of correctly predicted positive outcomes to the total quantity of data that should have been classed as positive is known as recall/sensitivity. The specificity metric measures the model's ability to identify negative classes correctly. Mathematically, the formulas of recall, precision, f1-score, and accuracy are shown below:

$$\text{Sensitivity (Recall)} = \frac{TP}{(FN+TP)} \tag{1}$$

$$\text{Precision} = \frac{TP}{(FP+TP)} \tag{2}$$

$$\text{F1-Score} = 2 \text{ x } \frac{(Precision \times Recall)}{(Precision + Recall)} \tag{3}$$

$$\text{Accuracy} = \frac{(TN+TP)}{(TN+FN+FP+TP)} \tag{4}$$

$$\text{Specificity} = \frac{TN}{(FP+TN)} \tag{5}$$

3 Results and Discussion

3.1 Results

The best model of the CNN1D algorithm with the addition of MFCC and CNN pure is obtained from testing hyperparameters and test sizes. To analyze this model, model evaluation was performed with test data to assess the model's ability to predict based on sound. A confusion matrix was used to evaluate the model and determine the performance parameters for each class and the overall average. The best result from testing the CNN1D algorithm with the addition of MFCC is the hyperparameter Adam with a learning rate of 0.001, epoch 300, and batch size 32. This model randomly uses a training test of 0.2 of the total dataset. The best result from testing the CNN1D algorithm without adding MFCC is the hyperparameter Adam with a learning rate of 0.001, epoch 300, batch size 16, and test size 0.4.

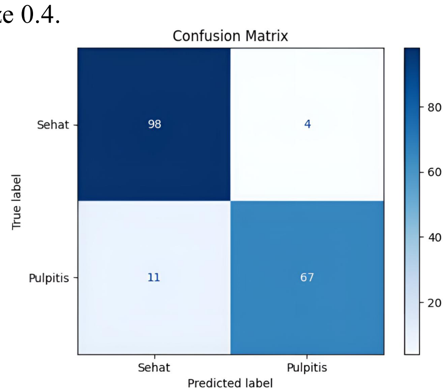

Figure 4. Confusion Matrix of model CNN with MFCC

Based on Figure 4. The confusion matrix shows that the model detected 98 "Sehat" samples correctly (True Negatives), while 4 "Sehat" samples were detected as "Pulpitis" (False Positives). In addition, the model detected 67 "Pulpitis" samples correctly (True Positives), but there were 11 "Pulpitis" samples detected as "Sehat" (False Negatives). This shows that the model has high accuracy in classifying both classes, with little error in predicting "Sehat" and "Pulpitis."

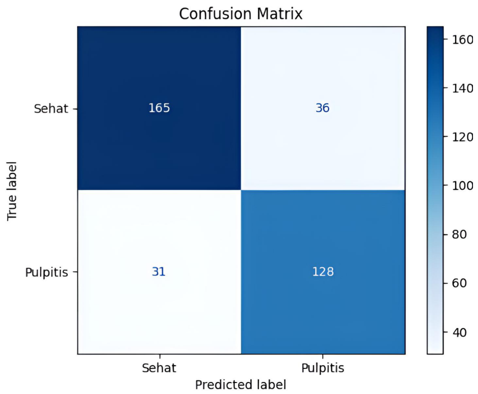

Figure 5. Confusion Matrix of model CNN only

Based on Figure 5. Based on the confusion matrix results, the pulpitis detection model performs well, with an accuracy of around 81.4%. From these results, there were 128 cases where the model correctly predicted that the tooth had pulpitis (True Positives) and 165 cases where the model correctly predicted that the tooth was healthy (True Negatives). However, there were also 36 cases where the model incorrectly predicted healthy teeth as pulpitis (False Positives) and 31 cases where the model incorrectly predicted teeth with pulpitis as healthy (False Negatives). The model's precision for detecting pulpitis is about 78%, meaning that 78% of the predictions are correct. Recall of the model for detecting pulpitis is about 81%, indicating that the model can detect about 81% of all correct pulpitis cases. F1-Score, the harmonic mean of precision and recall, was about 79%. Although these results indicate a reasonably good performance, further improvements can be achieved through the adjustment of hyperparameters, the use of data augmentation techniques, or an increase in the amount of training data.

Classification Report

	precision	recall	f1-score	support
Sehat	0.90	0.96	0.93	102
Pulpitis	0.94	0.86	0.90	78
accuracy			0.92	180
macro avg	0.92	0.91	0.91	180
weighted avg	0.92	0.92	0.92	180

Figure 6. Classification report of model CNN with MFCC

Figure 6 shows that the model has a precision of 0.90 for detecting "Sehat" samples and 0.94 for detecting "Pulpitis" samples. The recall for the "Sehat" sample was 0.96, meaning 96% of the "Sehat" samples were correctly detected, while the recall for the "Pulpitis" sample was 0.86, meaning 86% of the "Pulpitis" samples were correctly detected. The f1 score, the harmonic mean of recall and precision, was 0.93 for "Sehat" and 0.90 for "Pulpitis." Overall, the model had an accuracy of 0.92, with an average value (weighted average and macro average) for f1 score, recall, and precision of 0.92 each. This shows that the model has an excellent and balanced performance detecting both "Sehat" and "Pulpitis" classes.

Classification Report:

	precision	recall	f1-score	support
Sehat	0.84	0.82	0.83	201
Pulpitis	0.78	0.81	0.79	159
accuracy			0.81	360
macro avg	0.81	0.81	0.81	360
weighted avg	0.81	0.81	0.81	360

Figure 7. Classification report of model CNN only

Based on the classification report results in Figure 7, the pulpitis detection model performed exceptionally well, with an overall accuracy of 81%. The model showed a precision of 84% for the healthy teeth class, meaning 84% of the predicted healthy teeth were healthy. Recall for the healthy tooth class was 82%, indicating that the model successfully detected 82% of all actual healthy tooth cases. The F1-Score for this class was 83%, illustrating the balance between precision and recall. The model's precision was 78% for the pulpitis tooth class, meaning that 78% of the predictions were pulpitis. Recall for this class was 81%, indicating that the model successfully detected 81% of all actual pulpitis cases. The F1-Score for the pulpitis class was 79%, indicating a good balance between precision and recall for detecting pulpitis.

```
# Tampilkan hasil
print(f"Nilai Sensitivity (Recall) Model CNN MFCC: {results['Sensitivity (Recall)']:.2f}")
print(f"Nilai Specificity Model CNN MFCC: {results['Specificity']:.2f}")
print(f"Nilai Precision Model CNN MFCC: {results['Precision']:.2f}")
print(f"Nilai Recall Model CNN MFCC: {results['Recall']:.2f}")
print(f"Nilai F1-Score Model CNN MFCC: {results['F1-Score']:.2f}")
print(f"Nilai Accuracy Model CNN MFCC: {results['Accuracy']:.2f}")
```

```
Nilai Sensitivity (Recall) Model CNN MFCC: 0.86
Nilai Specificity Model CNN MFCC: 0.96
Nilai Precision Model CNN MFCC: 0.94
Nilai Recall Model CNN MFCC: 0.86
Nilai F1-Score Model CNN MFCC: 0.90
Nilai Accuracy Model CNN MFCC: 0.92
```

Figure 8. Performance of model CNN with MFCC

Figure 8 shows the model evaluation results with the addition of MFCC: The CNN MFCC model's sensitivity (recall) value is 0.86, specificity is 0.96, precision is 0.94, recall is 0.86, F1-Score is 0.90, and accuracy is 0.92. These metrics indicate that the model performs very well in detecting pulpitis in teeth based on audio signals.

```
# Tampilkan hasil
print(f"Nilai Sensitivity (Recall) Model CNN Only: {results['Sensitivity (Recall)']:.2f}")
print(f"Nilai Specificity Model CNN Only: {results['Specificity']:.2f}")
print(f"Nilai Precision Model CNN Only: {results['Precision']:.2f}")
print(f"Nilai Recall Model CNN Only: {results['Recall']:.2f}")
print(f"Nilai F1-Score Model CNN Only: {results['F1-Score']:.2f}")
print(f"Nilai Accuracy Model CNN Only: {results['Accuracy']:.2f}")
```

```
Nilai Sensitivity (Recall) Model CNN Only: 0.81
Nilai Specificity Model CNN Only: 0.82
Nilai Precision Model CNN Only: 0.78
Nilai Recall Model CNN Only: 0.81
Nilai F1-Score Model CNN Only: 0.79
Nilai Accuracy Model CNN Only: 0.81
```

Figure 9. Performance of model CNN only

Figure 9 shows. The printed evaluation results include various model performance metrics: Sensitivity (Recall), Specificity, Precision, Recall, F1-Score, and Accuracy. Each metric has a value displayed with two digits behind a comma. The values listed for each metric are Sensitivity (Recall) 0.81, Specificity 0.82, Precision 0.78, Recall 0.81, F1-Score 0.79, and Accuracy 0.81.

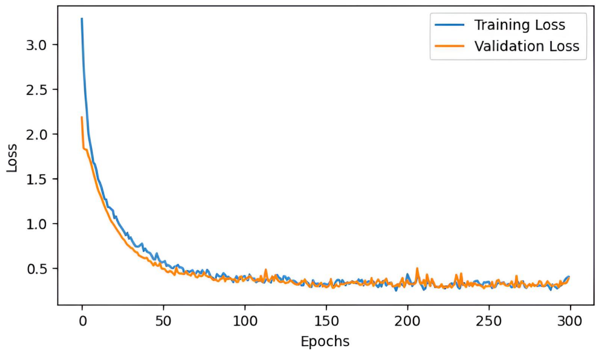

Figure 10. Graph of train loss and validation loss for model CNN MFCC

Figure 10 shows the loss graph for training data, represented by the blue line, and the orange line shows the loss graph for validation. At the beginning of training, the loss for training and validation drops rapidly. After about 50 epochs, the rate of loss decrease slows down, and both curves start to approach zero. At the end of the training, the training and validation losses are around shallow and stable values, indicating that the model has learned well without significant overfitting, as both curves remain aligned and do not deviate drastically.

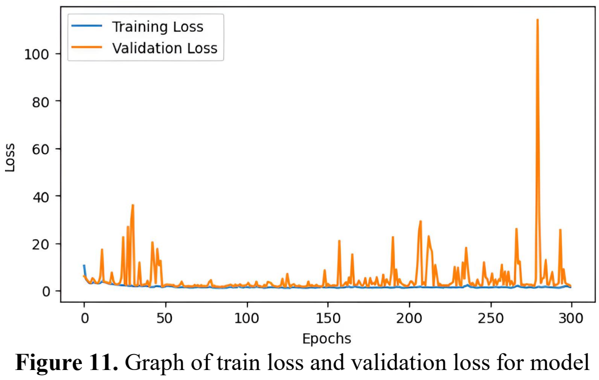

Figure 11. Graph of train loss and validation loss for model CNN only

Based on Figure 11. Shows the loss change in the machine learning model over 300 epochs. The blue curve represents training loss, while the orange curve represents validation loss. It can be seen that the training loss tends to decrease steadily over time, indicating that the model is getting better at learning its training data. In contrast, the validation loss shows considerable fluctuations, especially at the beginning and end of the epoch, indicating that the model faces an overfitting problem on the validation data. However, after about 100 epochs, the fluctuation of validation loss increases.

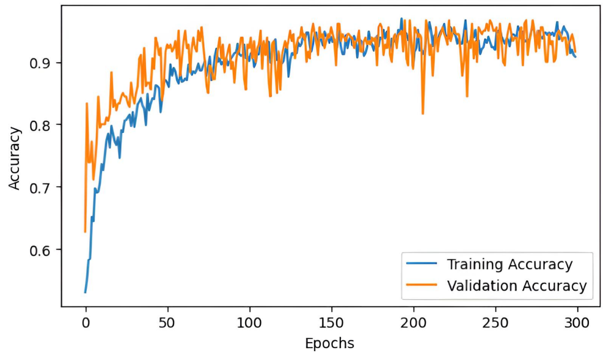

Figure 12. Graph of train accuracy and validation accuracy for CNN MFCC

Based on Figure 12. the accuracy graph for training data is represented by the blue line, and the orange line shows the accuracy graph for validation. At the beginning of training, both training and validation accuracies increase rapidly. After about 50 epochs, the rate of accuracy improvement slows down, and both curves start to approach the value of one. The training and validation accuracies fluctuate slightly throughout the training but remain high and stable, approaching the maximum value of 1.0. This shows that the model has good performance and strong generalization ability, as there is no significant difference between the training and validation accuracies.

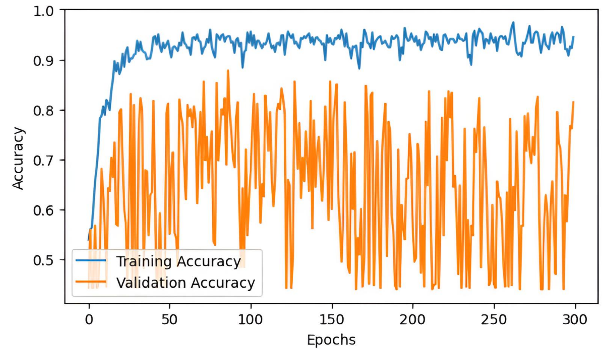

Figure 13. Graph of train accuracy and validation accuracy for CNN Only

Figure 13 shows the machine learning model's training and validation accuracy over 300 epochs. The blue line represents the training accuracy, which increases rapidly and stabilizes at around 90%. However, the orange line represents the validation accuracy, which shows enormous fluctuations and is unstable, hovering around 50-75% throughout the training. This shows that although the model performs well on the training data, it has difficulty generalizing to the validation data, which indicates overfitting.

Table 1. Prediction of CNN MFCC model directly against external data

No	Dentist Validation	Model Prediction	Marks
1	Sehat	Sehat	✓
2	Sehat	Sehat	✓
3	Sehat	Pulpitis	✗
4	Sehat	Sehat	✓

5	Sehat	Sehat	✓
6	Pulpitis	Sehat	✗
7	Pulpitis	Pulpitis	✓
8	Pulpitis	Pulpitis	✓
9	Pulpitis	Sehat	✗
10	Pulpitis	Pulpitis	✓

The table above shows the model's prediction results compared to the dentist's validation. Out of 10 trial runs, the model predicted the model incorrectly identified seven samples correctly and three samples. This result shows that the model accurately detects "Healthy" and "Pulpitis" conditions in these ten runs. The alignment between machine prediction and doctor validation indicates that the model learned the dataset well.

3.2 Discussion

Based on previous research, several areas for improvement must be improved regarding datasets and machine learning models. The limitations in previous research are related to datasets based on human speech. Human speech has much bias, be it between male and female voices or the voices of children and adults, so there is no homogenization between them.

This research has overcome and improved the limitations of previous research. We use the human teeth knock dataset to homogenize the data. Then, we combine two algorithms quite good at processing audio signals, MFCC and CNN1D. The model accuracy reaches 92%, as reflected in the classification report, and there is a very minimal loss.

4 Conclusion

According to the results and discussions, this research has successfully developed a system to detect pulpitis using machine learning with MFCC and CNN1D. The classification report demonstrates the model's good performance, which shows that it achieves 92% accuracy and good precision and recall values. This research only focuses on pulpitis detection; it is hoped that further research can detect dental diseases other than pulpitis through audio signals.

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