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Article

Tongue Detection For Identification Of Syndrome Diagnosis In Heart Disease Using Convolutional Neural Network

Niko Suwaryo [1], Koniasari [2], Amat Basri [3]

[1] *Universitas Medika Suherman, Bisnis Digital, Jawa Barat, Indonesia,*
[2] *Universitas Medika Suherman, Pengobatan Tradisional Tiongkok, Jawa Barat, Indonesia,*
[3] *Universitas Lia, System Informasi, Jakarta Selatan, Indonesia*

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CORRESPONDENCE

E-mail:
niko@medikasuherman.ac.id
niarobani04@gmail.com
av45ri@gmail.com

ABSTRACT

Convolutional Neural Network (CNN) which is one of the Deep Learning methods for Image identification and CNN models can identify images well but, in this case, it requires higher accuracy because the case is very crucial to determine the risk of heart disease. The initial stage in this study was the collection of tongue image data, 4836 training data and 1209 testing data. The image data used were the front, right side, left side of the tongue and under the tongue. The dataset was obtained from taking pictures using a smartphone camera centimeter above the object. The distribution of data in each class is shown in the following figure. The model from the two CNN algorithm experiments has accuracy performance. Based on the training results the model from the algorithm gets an accuracy value and testing by identifying 20% of the total dataset as test data. The identification results are formed in a Confusion Matrix to then be poured into a classification report and obtain: train loss 0.301446, train accuracy 0.862696, test loss 0.314132 and test accuracy 0.850290 so that from the results of the tongue data test it can be concluded that the accuracy value is quite good, above 80%.

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I. INTRODUCTION

The heart is a muscle that is divided into 4 chambers [1]. Two chambers are located at the top, namely the right and left atrium and two more chambers are located at the bottom, namely the right and left ventricles between the right and left chambers are separated by a muscle wall that functions to prevent the mixing of oxygen-rich blood with oxygen-poor blood [2]. Heart disease is a condition where the heart cannot carry out its duties properly, this disease occurs when blood to the heart muscle stops or is blocked, causing severe damage to the heart and causes of heart disease include heredity, age, gender, stress, lack of exercise, smoking, high cholesterol, hypertension, diabetes, and obesity [3]. Basically, heart disease can be prevented by various factors [4], including a healthy lifestyle, besides that, identification of heart disease syndrome diagnosis is also needed to prevent death in sufferers, one way to do tongue detection, early detection of heart disease is also needed to prevent death in sufferers. Symptoms caused by heart disease include discomfort in the chest, pain to the arms, pain radiating to the jaw or back and irregular heartbeat, digestive problems, dizziness, fatigue, frequent cold sweats, and a cough that stops from the role of the heart itself can circulate oxygen-rich blood to all parts of the body [5]. This is due to the lack of knowledge of the early symptoms of a disease that is lacking, the mindset of people who want to live a practical life, public awareness of health is still low, the lack of information delivery through the media about heart disease, and the lack of medical personnel are problems that are being faced in this case, so there needs to be an assistive media in the form of an easy system that provides the right solution to deal with these problems [6]. The early prevention application developed aims to help provide clear information for patients or the general public and for medical personnel it is hoped that it can help in handling it by providing the right solution, by only paying attention to the symptoms experienced [7]. The use of the convolutional neural network algorithm can be done to classify images or detect objects in the image [8], to find out the diagnosis of syndromes in heart disease, detect heart disease or not detected as having heart disease, image data processing that can be used from the problems above is the convolutional neural network algorithm [9]. Deep learning can learn its own computational methods using its own brain [10]. This deep learning technology is one of the most popular technologies for recognizing an activity or object that has a higher level of accuracy compared to previous machine methods [11]. To process datasets such as image classification, new techniques have been developed, namely deep learning techniques which are a combination of machine learning with artificial intelligence [12]. Increasing the accuracy in determining a disease is very important, because it can affect decision making on treatment and follow-up [13]. Automatic detection will contribute to reducing inequality, improving quality and optimizing the use of scarce medical resources. Computer science and medicine that can go beyond traditional medical imaging by combining these two fields with image data analysis and retrieval, multimedia and artificial intelligence [14]. Therefore, using deep learning is needed to solve this problem. The method that is suitable for applying the convolutional neural network algorithm.

II. LITERATURES REVIEW

Heart disease classification often faces challenges due to imbalanced datasets, where the number of instances in one class (e.g., healthy individuals) significantly outnumbers the other class (e.g., individuals with heart disease). This imbalance can lead to biased models that perform well on the majority class but poorly on the minority class, which is often the class of greater interest in medical diagnoses. To address this issue, a stacking algorithm was implemented in the study to improve classification performance.

The stacking algorithm is an ensemble learning technique that combines multiple base classifiers (such as decision trees, logistic regression, and support vector machines) to generate a stronger predictive model. The key idea is to train several models and then combine their outputs using a meta-classifier, which learns how to best aggregate the base model predictions.

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The results of the study demonstrated that the stacking algorithm significantly outperformed traditional single classifiers in handling the imbalanced dataset. The evaluation was based on several performance metrics, including:

- True Positive Rate (TPR): Measures the proportion of actual positives correctly identified.
- True Negative Rate (TNR): Assesses the model’s ability to correctly identify negative cases.
- Geometric Mean (G-Mean): A metric that balances TPR and TNR, making it effective for imbalanced data scenarios.
- Area Under the Curve (AUC): Reflects the model’s capability to distinguish between classes effectively.

The stacking algorithm produced higher TPR, TNR, G-Mean, and AUC scores compared to single classifiers, indicating its robustness in identifying heart disease cases even when faced with data imbalance. This improvement suggests that ensemble methods like stacking can play a crucial role in medical diagnosis systems, where accurate classification of minority classes (i.e., patients with heart disease) is vital.

Heart failure is a critical condition that requires early detection to improve patient outcomes. In this study, an Artificial Neural Network (ANN) model was developed to predict the likelihood of heart failure based on clinical and demographic data. ANNs are inspired by the human brain’s structure and function, capable of learning complex relationships within data through interconnected layers of neurons.

The ANN architecture used in this study consisted of:

- Two hidden layers: The first hidden layer contained 15 neuron units, while the second layer had 10 neuron units.
- Activation Functions: Likely used functions such as ReLU (Rectified Linear Unit) for hidden layers and sigmoid or softmax for the output layer to handle binary classification.
- Optimization Algorithm: The model may have been optimized using stochastic gradient descent or Adam optimizer to minimize the loss function effectively.

During model training and testing, the ANN demonstrated outstanding performance:

- Accuracy: The model achieved an impressive 92.032% accuracy on the testing dataset, indicating a high proportion of correct predictions.
- Area Under the Curve (AUC): The AUC value was 93%, showcasing the model’s strong discriminative ability to distinguish between heart failure and non-heart failure cases.

The high accuracy and AUC values suggest that the ANN model effectively captured the complex nonlinear patterns associated with heart failure risk factors. This predictive capability is crucial for clinical applications, enabling healthcare professionals to identify high-risk patients early and intervene proactively to prevent severe complications.

The integration of Deep Neural Networks (DNNs) with the Internet of Things (IoT) represents a transformative approach to healthcare, particularly in the early detection and monitoring of heart disease. This study explored the application of DNNs, leveraging IoT technology to enhance the accuracy and efficiency of heart disease prediction models.

IoT devices, such as wearable sensors, smartwatches, and health monitoring systems, were used to collect real-time physiological data, including heart rate, blood pressure, ECG signals, and activity levels. This continuous data stream provided a rich dataset for training the DNN model.

Key components of the methodology included:

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- Data Collection: IoT devices collected diverse health metrics from individuals, creating a large, real-time dataset.
- Preprocessing: Data cleaning and normalization were performed to ensure quality and consistency before feeding it into the DNN.
- DNN Architecture: The model likely consisted of multiple hidden layers with numerous neurons, allowing it to learn complex patterns and relationships in the health data.
- Training and Evaluation: The model was trained using backpropagation and optimized with algorithms such as Adam or RMSprop to improve learning efficiency.

The results showed that the DNN model, when combined with IoT data, provided accurate and effective heart disease predictions. Key performance highlights included:

- Improved Accuracy: The model achieved high predictive accuracy due to the richness of real-time data from IoT devices.
- Real-Time Monitoring: The IoT integration enabled continuous health monitoring, allowing for early detection of abnormal heart conditions.
- Visualization with Tableau: The study utilized Tableau, a data visualization tool, to present the predictive outcomes clearly. This visualization helped healthcare professionals interpret the results and make informed decisions quickly.

This approach underscores the potential of combining deep learning with IoT technologies to revolutionize heart disease management. By enabling real-time data analysis and predictive modeling, this system can support early intervention, reduce hospitalization rates, and improve patient outcomes in cardiac care.

III. METHODS

This research creates a framework that is useful as a in this study there is a research methodology which is the steps in compiling research starting from the planning process, data collection to making documentation. The flow of the methodology in this study is as follows:

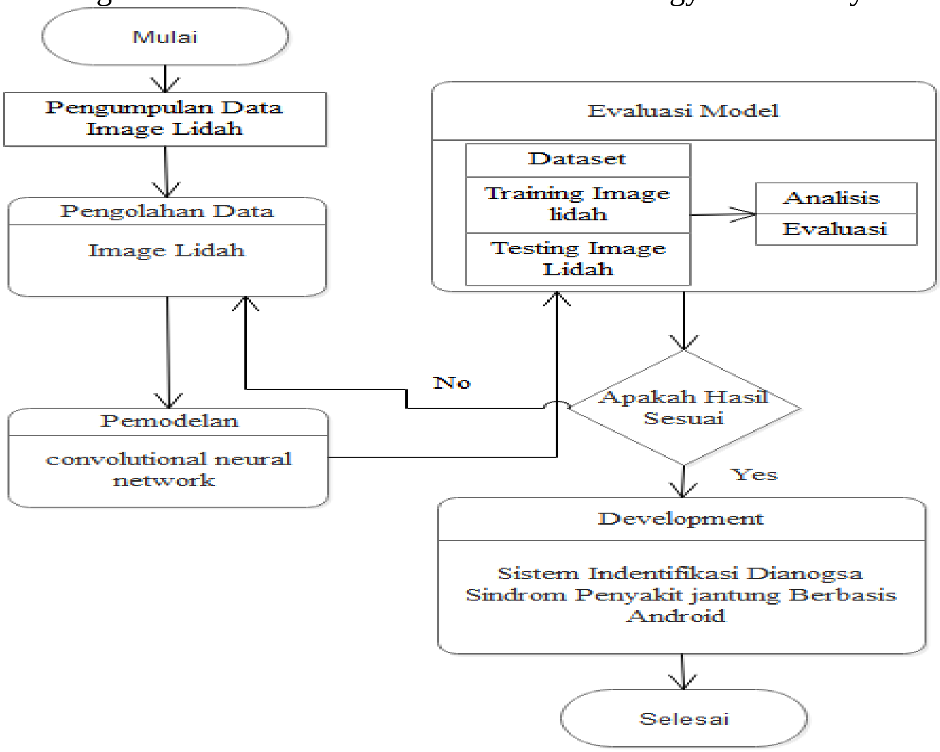

Figure 1. Description of the framework

Object of research

In general, research can be interpreted as a process of collecting and analyzing data that is carried out systematically and logically to achieve certain goals and enrich information and knowledge and unusual insights. Utilization of tongue photo data to find an identification of heart disease and the accuracy of the data, then to obtain this knowledge requires an effort to extract data through the stages of the method.

Research Stage

The research stage can be interpreted as a breakdown of a research process that aims to identify and evaluate the problems that occur. The stages below are the research stages.

1. Data collection
   The data used are tongue images obtained from the internet and sources who are patients with a history of heart disease. There are 202 Normal Heart data and 124 heart disease data. From these data, the data augmentation/generator process is then carried out to enrich the train dataset into 2,291 Normal Heart data and 3,125 heart disease data.
2. Algorithm
   The algorithm or method used is Convolutional Neural Network (CNN) which is one of the Deep Learning methods for Image identification [15].
3. Determination of Max_Features and N_Estimator
   There are no Max_Features and N_Estimator parameters in CNN. CNN uses a configuration in the form of a sequence of several layers such as convolutional layers, pooling layers, dropout layers, flatten layers, and fully connected layers
4. Training and model formation process
   a. Load dataset
   b. Perform preprocessing by changing the color format from BGR to RGB, then normalize the pixel values with a range of 0 to 1
   c. Split between train data and test data
   d. Build CNN model, and train model
   e. Test the accuracy of the model by creating a Confusion Matrix and Classification Report
5. Analysis of research results
   a. The analysis results contain several points that can affect model performance
   b. More specific training data (front or back of the tongue) to get better results
   c. Clearer training data focused on the image of the tongue and not too far away
   d. Training data that needs to be increased from source data for both normal heart conditions or heart disease
   e. Conducting several experiments on different model architectures
   f. Currently, 3 different architectures have been tried and quite significant differences have been obtained
   g. Adding iterations of the model training process (for now the iteration used is 30)

IV. RESULT

Data analysis

The initial stage in this study was the collection of tongue image data, 4836 training data and 1209 testing data. The image data used were the front, right side, left side of the tongue and under the tongue. The dataset was obtained from taking pictures using a smartphone camera \ centimeters above the object. The distribution of data in each class is shown in the following figure:

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Figure 2. Tongue Image

Analysis of Test Results

At this stage, an evaluation is carried out on the CNN model that has been created. Then, the results of the algorithm model will be applied to the application based on the highest accuracy value.

Figure 3. Tongue Image CNN Model

The code below is a code to display a graph showing the accuracy of the selected model, the graph shows how much accuracy the model has during training.

```
# membuat grafik model loss
plt.subplot(212)
plt.plot(history.history['loss'][:-5])
plt.plot(history.history['val_loss'][:-5])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.title("Model Loss", color='blue', fontsize=15)
# tampilkan grafik
plt.show()
# membuat grafik model accuracy
plt.subplot(212)
plt.plot(history.history['accuracy'][:-5])
plt.plot(history.history['val_accuracy'][:-5])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.title("Model Accuracy", color='blue', fontsize=15)
# tampilkan grafik
plt.show()
```

Figure 4. Code Model Accuracy

shows the accuracy graph during the training and validation process. Judging from the graph, the model is already a good fit, not experiencing overfitting or underfitting. This means that the model can run well without significant errors.

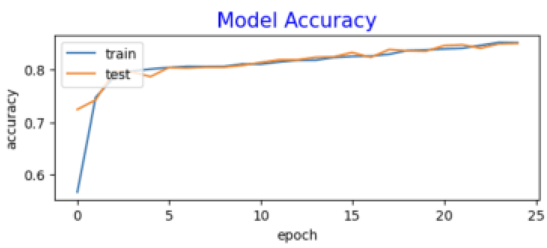

Figure 5. Model Accuracy

After the training process, the trained model in the training process is evaluated using validation data to get the final accuracy value. To evaluate the model against the test data, the code is as follows:

```
# pemanggilan fungsi load_model()
model = load_model(model_name)

# melakukan evaluasi terhadap model
score_train = model.evaluate(X_train, y_train, batch_size=32, verbose=0) # evaluasi skor data train
score_test  = model.evaluate(X_test, y_test, batch_size=32, verbose=0) # evaluasi skor data test

print('train loss    : %f' %score_train[0]) # nilai error dari evaluasi data latih
print('train accuracy: %f' %score_train[1]) # akurasi dari evaluasi data latih
print('test loss     : %f' %score_test[0]) # nilai error dari evaluasi data uji
print('test accuracy : %f' %score_test[1]) # akurasi dari evaluasi data uji
```


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Figure 6. Confusion Matrix

The model of the two CNN algorithm experiments has accuracy performance. Based on the training results, the model of the algorithm gets the accuracy value and testing by identifying 20% of the total dataset as test data. The identification results are formed in the Confusion Matrix to then be poured into the classification report and obtain, train loss 0.301446, train accuracy 0.862696, test loss 0.314132 and test accuracy 0.850290 so that from the results of the tongue data test it can be concluded that the accuracy value is quite good above 80%. The following is a table of classes and accuracy results.

Table 1. Accuracy

	Class	Precision	Sensitivity	Specificity	fpr	fnr	F1-score	pwc	accuracy	support
0	Jantung Normal	0.84	0.87	0.84	0.16	0.13	0.85	14.97	0.8503	595
1	Penyakit Jantung	0.87	0.84	0.87	0.13	0.16	0.85	14.97	0.8503	614

V. DISCUSSION

The Convolutional Neural Network (CNN) is highly effective in image classification tasks due to its ability to learn spatial features automatically. However, in the context of heart disease risk detection, where accuracy is critical for patient safety, achieving higher precision is essential. To improve performance, several strategies can be implemented. Advanced data preprocessing, such as normalization, contrast enhancement, and data augmentation, can help the model focus on relevant features. Optimizing the CNN architecture by experimenting with deeper networks like ResNet or VGGNet, and fine-tuning hyperparameters (learning rate, batch size, dropout rates) can enhance learning efficiency. Addressing class imbalance through resampling techniques or class weighting improves sensitivity to minority classes. Additionally, applying regularization methods (dropout, early stopping) reduces overfitting, while transfer learning leverages pre-trained models to boost performance with limited data. Finally, incorporating explainability techniques like Grad-CAM can help visualize model decisions, increasing trust in clinical applications. By combining these approaches, CNN models can achieve the high accuracy required for reliable heart disease diagnosis.

VI. CONCLUSION

The initial stage in this study was the collection of tongue image data, 4836 training data and 1209 testing data. The image data used were the front, right side, left side of the tongue and under the tongue. The dataset was obtained from taking pictures using a smartphone camera centimeter above the object. The distribution of data in each class is shown in the following figure. The model from the two CNN algorithm experiments has accuracy performance. Based on the training results, the model from the algorithm gets an accuracy value and testing by identifying 20% of the total dataset as test data. The identification results are formed in a Confusion Matrix to then be poured into the classification report and obtain: train loss 0.301446, train accuracy 0.862696, test loss 0.314132 and test accuracy 0.850290 so that from the results of the tongue data test it can be concluded that the accuracy value is quite good above 80%.

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BIOGRAPHY

Niko Suwaryo Graduated with a Bachelor's degree in Computer Science (S.Kom.) from Universitas Medika Suherman and later earned his Master's degree in Computer Science (M.Kom.) from the same university. He is currently a lecturer in the Department of Digital Business at Universitas Medika Suherman, Indonesia.

Koniasari Graduated with a Diploma in Acupuncture (AMd.Akup) and later earned a Bachelor's degree in Health Sciences (SST.) and a Master's degree in Health Sciences (M.Kes.) from Universitas Medika Suherman. She is currently a lecturer in the Department of Traditional Chinese Medicine at Universitas Medika Suherman, Indonesia.

Amat Basri Graduated with a Bachelor's degree in Computer Science (S.Kom.) from Universitas Lia and later earned his Master's degree in Computer Science (M.Kom.) from Universitas Medika Suherman. He is currently a lecturer in the Department of Information Systems at Universitas Lia, Jakarta, Indonesia.

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