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Comparison of Hyperparameter Optimization Techniques in Hybrid CNN-LSTM Model for Heart Disease Classification

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Abstract: Heart disease, which causes the highest number of deaths worldwide, recorded about 17.9 million cases in 2019, or about 32% of total global deaths, according to the World Health Organization (WHO). The significance of early detection of heart disease drives research to develop effective diagnosis systems utilizing machine learning. The advancement of machine learning in healthcare currently primarily serves as a supporting role in the ability of clinicians or analysts to fulfill their roles, identify healthcare trends, and develop disease prediction models. Meanwhile, deep learning has experienced rapid development and has become the most popular method in recent years, one of which is detecting diseases. The main objective of this research is to optimize the hybrid convolutional neural network (CNN) and long short-term memory (LSTM) model for classifying heart disease by comparing hyperparameter optimization using grid search and random search. Although random search requires less time in hyperparameter tuning, the classification performance results of grid search show higher accuracy. In the test, the hybrid CNN and LSTM model with grid search achieved 91.67% accuracy, 89.66% recall (sensitivity), 93.55% specificity, 92.86% precision, 91.23% f1-score, and 0.9310 AUC value. These results confirm that using a hybrid CNN and LSTM model with a grid search approach is better suited for classifying heart disease.

Keywords: Heart Disease; Machine Learning; Deep Learning; Classification; Hyperparameter Optimization

INTRODUCTION

Heart disease, a cause of high global mortality, accounted for 32% of the world's total deaths in 2019, according to data from the WHO (*Cardiovascular Diseases (CVDs)*, 2021). In Indonesia, the Institute for Health Metrics and Evaluation recorded a 1.25% increase in heart disease deaths per 100,000 population in 2019 compared to the previous year (Mustajab, 2023). Risk factors such as diabetes, high blood pressure, high cholesterol levels, abnormal pulse rate, and other factors make identifying heart disease difficult (Mohan et al., 2019).

An important first step in effective treatment is early identification of heart disease, which can reduce the risk of heart attack. While early detection can significantly improve patient survival, it is often difficult to do. Therefore, using machine learning (ML) based predictive models is gaining support from clinicians. The goal is to optimize heart disease detection, improve clinical decision-making efficiency, and reduce mortality (Mienye & Sun, 2021). The advancement of ML in the healthcare field, especially

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through disease prediction models, plays a supporting role in fulfilling the role of clinicians or analysts, identifying healthcare trends, and developing disease prediction models (Habehh & Gohel, 2021).

The importance of machine learning technology in healthcare is also reflected in deep learning (DL). DL, particularly convolutional neural network (CNN) and long short-term memory (LSTM), has become popular. With its ability to handle complex data and extract important features, CNN is suitable for diagnosing heart disease. Similarly, LSTM, a recurrent neural network (RNN), can communicate between units and store the necessary information (Sudha & Kumar, 2023). This research proposes using a hybrid CNN and LSTM model to improve the accuracy of heart disease classification, but to achieve optimal results, hyperparameter tuning is an important aspect.

In hyperparameter tuning, determining the optimal hyperparameter value is a challenging task. Adjusting each hyperparameter manually can be inefficient as it requires a lot of trial and error experiments, especially if there are many hyperparameters and the model is quite complex (Yang & Shami, 2020). Therefore, several hyperparameter optimization techniques have been developed to overcome these obstacles. Among them are the grid search method and the random search method. With these techniques, hyperparameter tuning can be done more efficiently and support better model development (Ali et al., 2023). Based on studies that have been conducted concerning similar theories, one of them is research conducted by (Sunarya & Haryanti, 2022), which compares the performance of optimization algorithms in the random forest (RF) method to detect heart failure and obtain an accuracy result of 85.63%. On the other hand, (Gunawan et al., 2020) also conducted a similar study using the grid search to improve the accuracy of predicting diabetes mellitus disease in the logistic regression (LR) algorithm. By using this method, there was an increase in accuracy from 80% to 83.33%.

This research specifically focuses on comparing hyperparameter optimization using grid search and random search methods to improve model performance in classifying heart disease in hybrid model CNN and LSTM. Model performance analysis considers various evaluation metrics, including accuracy, precision, sensitivity or recall, specificity, f1-score, and area under the Receiver Operating Characteristic curve (ROC/AUC). With this approach, this research can improve the overall experimental results and significantly contribute to developing more complex classification models in diagnosing heart disease.

LITERATURE REVIEW

There are various studies related to heart disease classification and those related to hyperparameter optimization that researchers with various techniques have proposed. In this study, some existing ML and DL-based diagnosis techniques are presented to explain the importance of the proposed research. Research conducted by (Wiharto et al., 2022) used deep neural network (DNN) by applying feature selection on the Z-Alizadeh Sani dataset. From the method used in this study, the AUC performance was obtained at 93.7%, with an accuracy of 87.7% and sensitivity of 87.7%.

The study used the Korean National Insurance Service database by (Lee et al., 2022) with 2,037,027 samples to compare and validate the logistic regression (LR) model with DNN regarding predicting cardiovascular disease mortality and hospitalization with hypertension. The proposed method showed superior performance of DNN in all datasets with 86.3% accuracy; f1-score 85.4%; AUC 93.2% in predicting hospitalization due to cardiovascular disease and death due to cardiovascular disease with 92.5% accuracy; f1-score 92.4%; AUC 97.9%. Another study used the UCI heart disease public dataset, with 14 attributes and 1050 samples (Arooj et al., 2022). The research employed a deep convolutional neural network (DCNN) to differentiate whether a particular instance is healthy or affected by heart disease and obtained validation performance accuracy of 91.71%, precision of 88.88%, recall of 82.75%, and f1-score of 85.70%. of 82.75%, and f1-score of 85.70%.

Other research conducted uses the CNN algorithm to predict heart disease. The dataset used is structured and unstructured patient data. The developed model produces accuracy performance ranging from 85-88% (Shankar et al., 2020). Another study on heart disease prediction (Sudha & Kumar, 2023) used a hybrid CNN and LSTM algorithm with the Cleveland Clinic Foundations dataset. The method was validated using the k-fold cross-validation, resulting in an accuracy performance of 89%. Research conducted by (Shrivastava et al., 2023) used a hybrid CNN and BiLSTM algorithm to predict heart disease by applying feature selection. The study used the UCI Cleveland heart disease dataset. The

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proposed method obtained an accuracy performance of 96.66%. In another study using the same dataset, different ML algorithms and ensemble models were evaluated for their accuracy on a specific task. The study showed the accuracy performance results of random forest (RF) is 83.6%, support vector machine (SVM) is 81.3%, k-nearest neighbors (KNN) at 82.8%, gated recurrent unit (GRU) is 81.46%, and long-short-term memory (LSTM) of 81.31% (Javid et al., 2020).

In addition, research that discusses hyperparameter optimization was conducted by (Sunarya & Haryanti, 2022) and (Gunawan et al., 2020). (Sunarya & Haryanti, 2022) comparing grid search, bayesian search, and random search optimization algorithms in the RF method to detect heart failure with the dataset used is the Heart Failure Clinical Records Dataset. The study results showed that RF with random search achieved the highest performance with an average accuracy of 85.63%, precision of 87.38%, and recall of 85.63% and could increase accuracy by 7.7% from RF without using optimization algorithms. A study by (Gunawan et al., 2020) proposed the LR algorithm to predict diabetes mellitus disease. The grid search method is also used to optimize the model. The results showed that grid search can improve the accuracy performance of the model to 80%, and the accuracy performance of the data checking showed 83.33%.

Based on the given literature study, this research is based on existing methods and algorithms. However, this research tries to improve what has been obtained previously, such as compared to research conducted by (Sudha & Kumar, 2023), where hyperparameter tuning was carried out manually and research conducted by (Gunawan et al., 2020), where hyperparameter tuning was carried out by grid search technique. This research optimizes model hyperparameters the model by comparing grid search and random search hyperparameter tuning techniques. In addition, compared to research conducted by (Sunarya & Haryanti, 2022), this research focuses on using the UCI Cleveland heart disease dataset and a hybrid CNN-LSTM algorithm in modeling.

METHOD

The overall research flow of the proposed method can be seen in Figure 1, which uses four primary methodologies: data preprocessing, modeling using a hybrid CNN-LSTM architecture, optimizing hyperparameter tuning, and evaluating the model's performance.

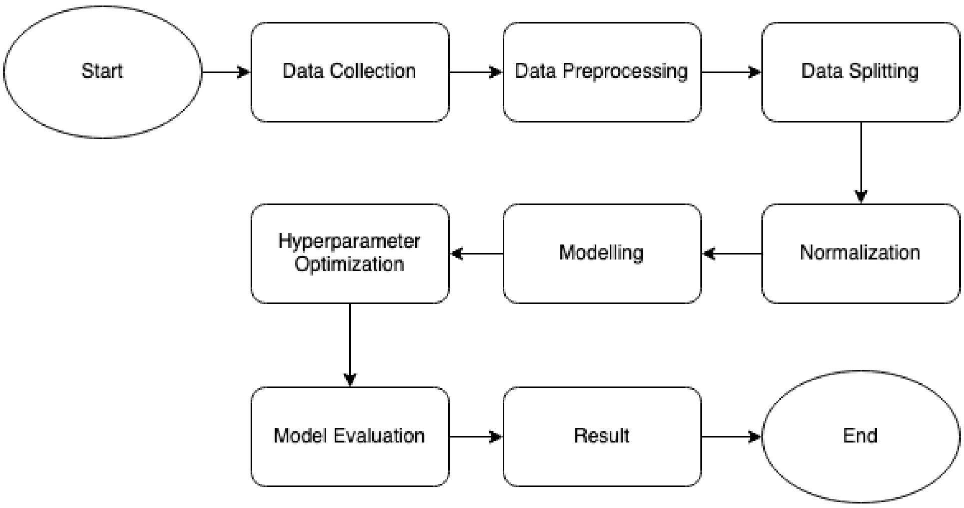

Fig. 1 Research Flow

Data Collection

This research employs the Heart Disease Cleveland Dataset, a public dataset on heart disease obtained from the machine learning repository at the University of California, Irvine (UCI) (Sarra et al., 2023). The dataset, comprising 303 data entries and 76 attributes, provides a comprehensive source for investigating heart disease patterns (Janosi et al., 1988). Notably, the published studies focus on 14 specific attributes within the dataset, of which 13 columns serve as features, while 1 column is

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designated as the target variable. For a more detailed understanding of the dataset's characteristics, refer to Table 1.

Table 1 Dataset Attributes

Attributes	Description	Type
age	Age in years	Integer
sex	gender	Categorical
cp	Chest pain type	Categorical
tretsbps	Resting blood in pressure	Integer
chol	Cholesterol level	Integer
fbs	Fasting blood sugar	Categorical
restecg	Resting electrocardiographic results	Categorical
thalach	Maximum heart rate	Integer
exang	Exercise-induced angina	Categorical
oldpeak	ST depression	Integer
slope	ST segment	Categorical
ca	Number of major vessel (0-3) by flourosopy	Integer
thal	3: normal; 6: fixed defect; 7: reversable defect	Categorical
num	Diagnosis of heart disease	Integer

Data Preprocessing

The stage after obtaining the dataset is data preprocessing. Raw data that is not ready to be used is first converted into more helpful information and can later be processed further from data preprocessing to the modeling stage using the Python language for all processing. In carrying out the data preprocessing stage in this research, there are two steps: data cleansing and data conversion.

Data cleansing is used to maintain the data quality used in the analysis. Data cleansing is required to find and eliminate unused, irrelevant, or missing variables and values. The data used later does not contain empty or null values; it is clean and ready to be used in the following process. In the data set, there were six missing values; data deletion was performed to handle the missing values (Mohan et al., 2019).

The next step is to perform data conversion, which converts the original multi-class target into a binary class. The target data on the UCI Heart Disease dataset has 5 classes with values (0, 1, 2, 3, and 4), where 0 indicates the absence of heart disease, and 1, 2, 3, and 4 indicate the presence of heart disease. However, only target values 0 and 1 were used in this study. Classes 1, 2, 3, and 4 are converted to 1 to detect the presence or absence of heart disease (Louridi et al., 2021).

Data Splitting

The heart disease UCI dataset that has previously been preprocessed, as described in the previous subchapter, is then carried out data splitting to divide the dataset into training data and testing data with a range adjusted to the research needs and objectives. This study divides the dataset into 80% for training data and 20% for testing data. The original data amounted to 297, distributed into 237 for training data and 60 for testing data. The training data is used in the hyperparameter optimization process on the hybrid CNN and LSTM model to get the optimal hyperparameter value. Part of the training data is used to validate the model's performance in the hyperparameter tuning process using the cross-validation method (Joseph & Vakayil, 2022). Furthermore, the performance of the hyperparameter-optimized model through grid search and random search was evaluated using test data.

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Normalization

Data normalization is essential in data analysis because variations in the range between features in a dataset can cause bias. The data normalization process is performed using the min-max scaling technique. In min-max scaling, data values are adjusted to range between 0 and 1, with 0 being the minimum value and 1 being the maximum value. The remaining range of data values is represented in decimal form, spanning the range of 0 to 1 (Obayya et al., 2023). The results of before and after data normalization can be seen in Figures 2 and 3. The following are details of the functions performed by the min-max scaling in normalizing the data:

$$\chi_{scaled} = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
48.0	1.0	2.0	110.0	229.0	0.0	0.0	168.0	0.0	1.0	3.0	0.0	7.0
44.0	0.0	3.0	108.0	141.0	0.0	0.0	175.0	0.0	0.6	2.0	0.0	3.0
77.0	1.0	4.0	125.0	304.0	0.0	2.0	162.0	1.0	0.0	1.0	3.0	3.0
61.0	1.0	4.0	138.0	166.0	0.0	2.0	125.0	1.0	3.6	2.0	1.0	3.0
71.0	0.0	2.0	160.0	302.0	0.0	0.0	162.0	0.0	0.4	1.0	2.0	3.0

Fig. 2 Dataset before Normalization

age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal
0.395833	1.0	0.333333	0.150943	0.235160	0.0	0.0	0.701754	0.0	0.161290	1.0	0.000000	1.0
0.312500	0.0	0.666667	0.132075	0.034247	0.0	0.0	0.763158	0.0	0.096774	0.5	0.000000	0.0
1.000000	1.0	1.000000	0.292453	0.406393	0.0	1.0	0.649123	1.0	0.000000	0.0	1.000000	0.0
0.666667	1.0	1.000000	0.415094	0.091324	0.0	1.0	0.324561	1.0	0.580645	0.5	0.333333	0.0
0.875000	0.0	0.333333	0.622642	0.401826	0.0	0.0	0.649123	0.0	0.064516	0.0	0.666667	0.0

Fig. 3 Dataset after Normalization

Modelling

The modeling step involves developing a model from TensorFlow with a hybrid architecture of CNN and LSTM, as shown in Figure 4. CNN is one of the most well-known and commonly used DL algorithms. The structure of CNN is inspired by neurons in humans and animals, similar to neural network. One of the advantages of CNN is that it can automatically identify relevant features. Various fields have applied CNN algorithms, such as computer vision, speech recognition, and others (Alzubaidi et al., 2021). LSTM is a subset of RNN designed for long-term learning, with its ability to create loops in the network, allowing for significant information retention over time. With all gates, including input gates, receiving information from previous timestamps and integrating it into the calculations for the next timestamp, the LSTM model ensures that prior knowledge is retained and utilized in future predictions (Van Houdt et al., 2020).

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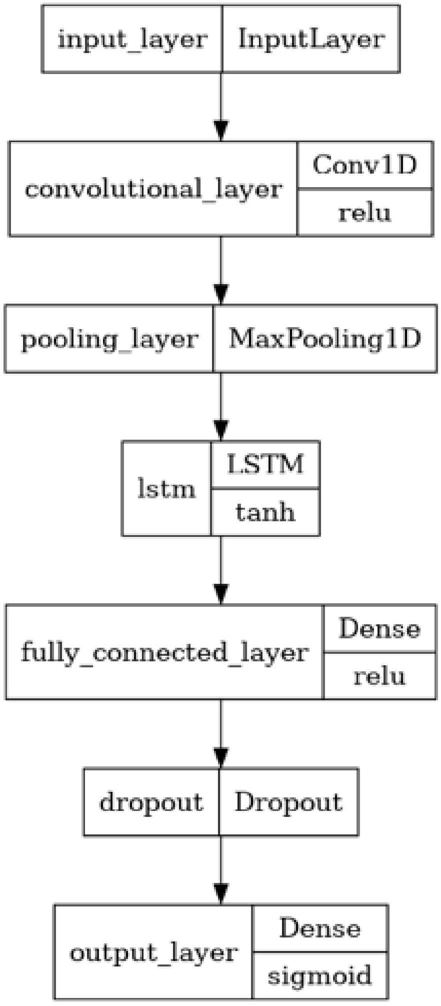

Fig. 4 Hybrid CNN-LSTM Architecture

Based on Figure 4, the CNN-LSTM hybrid architecture comprises the input layer, one-dimensional convolutional layer, one-dimensional pooling layer, LSTM layer, fully connected layer, and output layer. Based on the 13 features used in the dataset, the input layer receives 13. The convolutional and fully connected layers use the Rectified Linear Units (ReLu) activation function. The LSTM part uses the tanh function, while the output layer uses a sigmoid function to classify whether the data belongs to the heart disease class or not heart disease. In the fully connected layer, a dropout is added to prevent overfitting of the model (Anggraini Susanti et al., 2023).

Hyperparameter Optimization

This stage aims to improve the model's performance in predicting new data. Optimizing hyperparameters is conducted through suitable methods, such as grid search and random search. Grid search parameters are often called exhaustive search models on each hyperparameter combination. Each parameter variation is tried to produce the best combination of values (Wresti et al., 2022). Random search works by trying each value of the parameter value combination randomly. The random search seeks the optimal along the parameter values clearly defined between the lower and upper limits (Sunarya & Haryanti, 2022). Table 2 shows the parameters such as dropout, batch size, number of hidden units in dense and LSTM, number of filters, and epochs optimized with grid search and random search.

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Table 2 Hyperparameter Search Space

Hyperparameter	Values
Filters	[32, 64, 128]
Units of LSTM	[32, 64, 128]
Units of Dense	[32, 64, 128]
Dropout rate	[0.2, 0.5]
Epochs	[50, 100]
Batch size	[8, 16, 32]

Model Evaluation

Model evaluation is an essential step in understanding the extent to which a model can perform classification accurately. In this context, the confusion matrix is a handy instrument to illustrate model performance. There are four main components of the confusion matrix, namely true positive (TP), true negative (TN), false positive (FP), and false negative (FN). When there is a correct prediction for positive data, the term is TP; otherwise, if the prediction is inaccurate, it is called FN. When there is a correct prediction for negative data, TN is used, while FP occurs if the prediction is inaccurate.

Common parameters like accuracy, precision, recall (sensitivity), specificity, and f1-score are typical metrics employed for assessing the performance of a model. Accuracy is the ratio of correctly classified data to the overall data. Precision is the ratio of true positive compared to the total positive predicted results. Recall is the ratio of true positive predictions compared to the overall positive true data. Specificity is the correctness of negative predictions compared to the overall classified as negative data, while f1-score is a weighted average comparison of precision and recall (Hicks et al., 2022). In addition, ROC/AUC is also obtained based on the confusion matrix. AUC is the area under the ROC line. ROC is a piecewise linear curve that plots the true positive rate against the false positive rate. The AUC score is 0.5 - 1; the closer it is to 1, the better the score (Gneiting & Walz, 2022). The formula for the performance metrics is as follows:

$$Accuracy = \frac{(TP + \mathrm{TN})}{(\mathrm{TP + FP + FN + TN})} \tag{2}$$

$$Precision = \frac{TP}{(\mathrm{TP + FP})} \tag{3}$$

$$Recall = \frac{TP}{(\mathrm{TP + FN})} \tag{4}$$

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

$$F1 - score = 2 \times \frac{(Recall \times \mathrm{Precision})}{(\mathrm{Recall+Precision})} \tag{6}$$

RESULT

Model Hyperparameter Optimization

In optimizing the hyperparameters for the hybrid CNN and LSTM model, the grid search method explores all possible hyperparameter combinations within the search space. The evaluation was performed with 5-fold cross-validation with a time requirement of 11797 seconds. Besides, in optimizing hyperparameters for the hybrid CNN and LSTM model through the random search approach, the combination of hyperparameters is randomly selected from the search space. Then, the random search attempted a maximum of 150 hyperparameter combinations, and the entire random search phase lasted for 8949 seconds, with the evaluation conducted through 5-fold cross-validation. The results of comparing the optimal hyperparameters for each technique are presented in Table 3.

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Table 3 Comparison of Hyperparameter Results

Techniques	Filters	Units of LSTM	Units of Dense	Dropout rate	Epochs	Batch Size
Grid Search	64	128	32	0.2	100	8
Random Search	128	128	128	0.2	100	16

Model Performance Evaluation

Following multiple processes, this phase describes the outcomes of heart disease classification using hyperparameters acquired earlier through grid search optimization and random search optimization. The confusion matrix provides results that can be seen in Figure 5 and Figure 6.

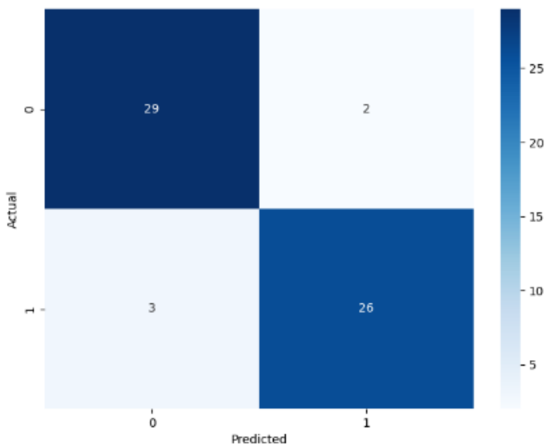

Fig. 5 Confusion Matrix of Grid Search

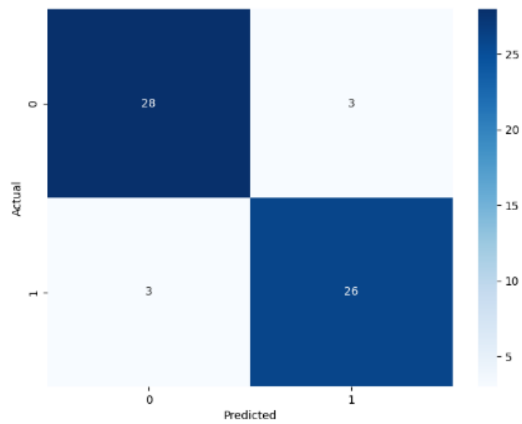

Fig. 6 Confusion Matrix of Random Search

Based on Figures 5 and 6, the hybrid CNN-LSTM model with grid search optimization has a True Positive of 26, False Positive of 2, True Negative of 29, and False Negative of 3. Meanwhile, the model with random search optimization has a True Positive of 26, False Positive of 3, True Negative of 28, and False Negative of 3. Both models can detect target classes TP and non-target classes TN well and have little error in predicting target classes as non-targets FN and predicting non-target classes as targets FP. The confusion matrix produces TP, TN, FP, and FN values, which are then utilized in the calculation of accuracy, sensitivity, specificity, precision, and f1-score. The evaluation comparison for each technique is presented in Table 4.

Table 4 Comparison of Performance Results

Techniques	Accuracy	Precision	Recall	Specificity	F1-score
Grid Search	91.67%	92.86%	89.66%	93.55%	91.23%
Random Search	90%	89.66%	89.66%	90.32%	89.66%

The effectiveness of the hybrid CNN and LSTM model using both grid search and random search was also assessed through ROC curves. These curves depict the ratio of the true positive rate to the false positive rate. The ROC curves of the hybrid CNN and LSTM model employing both grid search and random search are shown in Figures 7 and 8.

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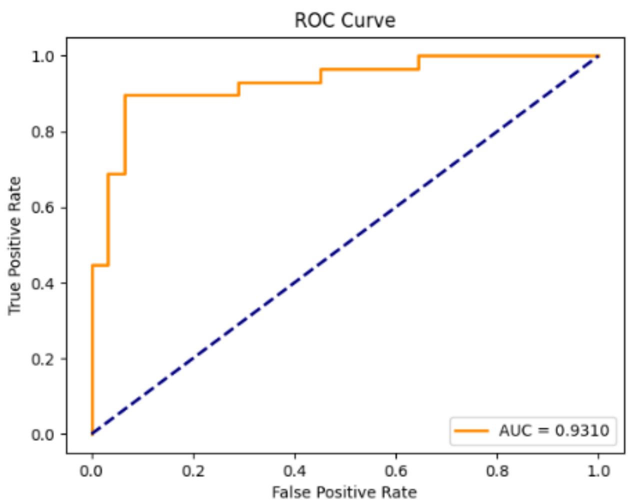

Fig. 7 ROC Curve of Grid Search

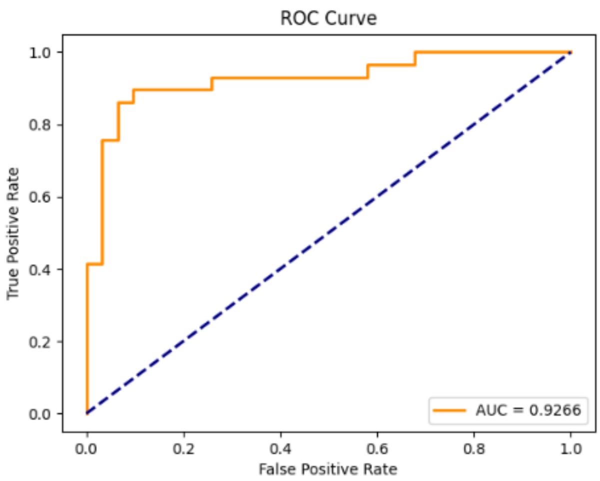

Fig. 8 ROC Curve of Random Search

Based on Figure 7, the CNN-LSTM hybrid model with grid search obtained an AUC value of 0.9310. Meanwhile, based on the curve in Figure 8, the CNN-LSTM hybrid model with random search gets an AUC value of 0.9266. Therefore, the CNN and LSTM hybrid model with grid search has higher accuracy than the random search technique because the AUC value of grid search is higher and nearer to 1, which means a low false positive rate and a high true positive rate.

DISCUSSIONS

Hyperparameter optimization using grid search gave the most outstanding results in this study. Various metrics accuracy, precision, recall, specificity, f1-score, and AUC, are used to evaluate the effectiveness of the hybrid CNN and LSTM model. The evaluation results using testing data showed that the model achieved an accuracy of 91.67%, precision of 92.86%, recall of 89.66%, specificity of 93.55%, f1-score of 91.23%, and AUC value of 93.10%. Although the study (Shrivastava et al., 2023) achieved a higher accuracy value of about 5% compared to this study, the research conducted by (Shrivastava et al., 2023) applied feature selection techniques to the dataset, while this study focuses on hyperparameter optimization. On the other hand, compared to (Shankar et al., 2020), (Sudha & Kumar, 2023), and (Javid et al., 2020), this study achieved higher accuracy and gain of about 2.67% to 10.36%. With these promising results, it is possible to develop the proposed method further, which can be used to classify heart diseases.

CONCLUSION

In this research, the DL technique is performed using a hybrid architecture of CNN and LSTM to detect heart disease. Hyperparameter optimization uses grid and random search to get the optimal hyperparameter. Although grid search takes longer than random search, the classification performance of the CNN and LSTM hybrid model with grid search is higher than with random search. The test results showed accuracy of 91.67%, precision of 92.86%, recall of 89.66%, specificity of 93.55%, f1-score of 91.23%, and AUC value of 93.10%. Based on these results, CNN and LSTM architectures with grid search optimization are better used in classifying heart disease. This model can help healthcare providers diagnose heart disease patients more accurately by improving diagnostic accuracy. Apart from that, for further development, this research suggests exploring alternative DL classification algorithms, investigating the feature selection stage for more optimal outcomes, exploring the preprocessing step for more optimal results, and using other hyperparameter optimization techniques.

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p-ISSN : 2541-044X

REFERENCES

Ali, Y. A., Awwad, E. M., Al-Razgan, M., & Maarouf, A. (2023). Hyperparameter Search for Machine Learning Algorithms for Optimizing the Computational Complexity. *Processes*, *11*(2). https://doi.org/10.3390/pr11020349

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M. A., Al-Amidie, M., & Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*, *8*(1). https://doi.org/10.1186/s40537-021-00444-8

Anggraini Susanti, L., Soleh, A. M., Sartono, B., Pertanian Bogor, I., & Korespondensi, P. (2023). DEEP LEARNING IMAGE CLASSIFICATION RONTGEN DADA PADA KASUS COVID-19 MENGGUNAKAN ALGORITMA CONVOLUTIONAL NEURAL NETWORK. *Jurnal Teknologi Informasi Dan Ilmu Komputer (JTIIK)*, *10*. https://doi.org/10.25126/jtiik.2023107142

Arooj, S., Rehman, S. ur, Imran, A., Almuhaimeed, A., Alzahrani, A. K., & Alzahrani, A. (2022). A Deep Convolutional Neural Network for the Early Detection of Heart Disease. *Biomedicines*, *10*(11). https://doi.org/10.3390/biomedicines10112796

Cardiovascular diseases (CVDs). (2021, June 11). https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

Gneiting, T., & Walz, E. M. (2022). Receiver operating characteristic (ROC) movies, universal ROC (UROC) curves, and coefficient of predictive ability (CPA). *Machine Learning*, *111*(8), 2769–2797. https://doi.org/10.1007/s10994-021-06114-3

Gunawan, M. I., Sugiarto, D., & Mardianto, I. (2020). JEPIN (Jurnal Edukasi dan Penelitian Informatika) Peningkatan Kinerja Akurasi Prediksi Penyakit Diabetes Mellitus Menggunakan Metode Grid Seacrh pada Algoritma Logistic Regression. *JEPIN (Jurnal Edukasi Dan Penelitian Informatika)*, *6*.

Habehh, H., & Gohel, S. (2021). Machine Learning in Healthcare. *Current Genomics*, *22*(4), 291–300. https://doi.org/10.2174/1389202922666210705124359

Hicks, S. A., Strümke, I., Thambawita, V., Hammou, M., Riegler, M. A., Halvorsen, P., & Parasa, S. (2022). On evaluation metrics for medical applications of artificial intelligence. *Scientific Reports*, *12*(1). https://doi.org/10.1038/s41598-022-09954-8

Janosi, A., Steinbrunn, W., Pfisterer, M., & Detrano, R. (1988, June 30). *Heart Disease*. UCI Machine Learning Repository.

Javid, I., Khalaf, A., Alsaedi, Z., & Ghazali, R. (2020). Enhanced Accuracy of Heart Disease Prediction using Machine Learning and Recurrent Neural Networks Ensemble Majority Voting Method. In *IJACSA) International Journal of Advanced Computer Science and Applications* (Vol. 11, Issue 3). www.ijacsa.thesai.org

Joseph, V. R., & Vakayil, A. (2022). SPlit: An Optimal Method for Data Splitting. *Technometrics*, *64*(2), 166–176. https://doi.org/10.1080/00401706.2021.1921037

Lee, S. J., Lee, S. H., Choi, H. I., Lee, J. Y., Jeong, Y. W., Kang, D. R., & Sung, K. C. (2022). Deep Learning Improves Prediction of Cardiovascular Disease-Related Mortality and Admission in Patients with Hypertension: Analysis of the Korean National Health Information Database. *Journal of Clinical Medicine*, *11*(22). https://doi.org/10.3390/jcm11226677

Louridi, N., Douzi, S., & El Ouahidi, B. (2021). Machine learning-based identification of patients with a cardiovascular defect. *Journal of Big Data*, *8*(1). https://doi.org/10.1186/s40537-021-00524-9

Mienye, I. D., & Sun, Y. (2021). Improved heart disease prediction using particle swarm optimization based stacked sparse autoencoder. *Electronics (Switzerland)*, *10*(19). https://doi.org/10.3390/electronics10192347

Mohan, S., Thirumalai, C., & Srivastava, G. (2019). Effective heart disease prediction using hybrid machine learning techniques. *IEEE Access*, *7*, 81542–81554. https://doi.org/10.1109/ACCESS.2019.2923707

Mustajab, R. (2023, September 29). *Kematian akibat Penyakit Jantung di Indonesia Terus Meningkat*. https://dataindonesia.id/kesehatan/detail/kematian-akibat-penyakit-jantung-di-indonesia-terus-meningkat

*name of corresponding author

e-ISSN : 2541-2019
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Obayya, M., Alsamri, J. M., Al-Hagery, M. A., Mohammed, A., & Hamza, M. A. (2023). Automated Cardiovascular Disease Diagnosis Using Honey Badger Optimization with Modified Deep Learning Model. *IEEE Access*, *11*, 64272–64281. https://doi.org/10.1109/ACCESS.2023.3286661

Sarra, R. R., Dinar, A. M., & Mohammed, M. A. (2023). Enhanced accuracy for heart disease prediction using artificial neural network. *Indonesian Journal of Electrical Engineering and Computer Science*, *29*(1), 375–383. https://doi.org/10.11591/ijeecs.v29.i1.pp375-383

Shankar, V. V., Kumar, V., Devagade, U., Karanth, V., & Rohitaksha, K. (2020). Heart Disease Prediction Using CNN Algorithm. *SN Computer Science*, *1*(3). https://doi.org/10.1007/s42979-020-0097-6

Shrivastava, P. K., Sharma, M., sharma, P., & Kumar, A. (2023). HCBiLSTM: A hybrid model for predicting heart disease using CNN and BiLSTM algorithms. *Measurement: Sensors*, *25*. https://doi.org/10.1016/j.measen.2022.100657

Sudha, V. K., & Kumar, D. (2023). Hybrid CNN and LSTM Network For Heart Disease Prediction. *SN Computer Science*, *4*(2). https://doi.org/10.1007/s42979-022-01598-9

Sunarya, U., & Haryanti, T. (2022). Perbandingan Kinerja Algoritma Optimasi pada Metode Random Forest untuk Deteksi Kegagalan Jantung. *Jurnal Rekayasa Elektrika*, *18*(4). https://doi.org/10.17529/jre.v18i4.26981

Van Houdt, G., Mosquera, C., & Nápoles, G. (2020). A review on the long short-term memory model. *Artificial Intelligence Review*, *53*(8), 5929–5955. https://doi.org/10.1007/s10462-020-09838-1

Wiharto, Suryani, E., Setyawan, S., & Putra, B. P. (2022). The Cost-Based Feature Selection Model for Coronary Heart Disease Diagnosis System Using Deep Neural Network. *IEEE Access*, *10*, 29687–29697. https://doi.org/10.1109/ACCESS.2022.3158752

Wresti, Gunawan, Purwanto, & Catur Supriyanto. (2022). Comparison of Grid Search and Evolutionary Parameter Optimization with Neural Networks on JCI Stock Price Movements during the Covid 19. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, *6*(6), 1079–1087. https://doi.org/10.29207/resti.v6i6.4402

Yang, L., & Shami, A. (2020). On hyperparameter optimization of machine learning algorithms: Theory and practice. *Neurocomputing*, *415*, 295–316. https://doi.org/10.1016/j.neucom.2020.07.061

*name of corresponding author