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Evaluating the Effectiveness of Machine Learning for Heart Disease Prediction in Healthcare Sector

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Abstract

Heart disease is still one of the world's top causes of mortality. Thus, prevention and effective treatment depend on early detection. This study uses the Cleveland Heart Disease Dataset to examine how ML techniques can be used in the prediction of heart disease. By removing outliers, encoding categorical data, handling missing values, and scaling features, the dataset was prepared for further processing. There was an 80:20 split between the data sets used for training and testing. Data was collected and used to train and assess a number of classification models. These models included DT, SVM, RF, and ANN. In comparison to the other models, the ANN performed quite well, achieving 86% accuracy, 86% precision,84% recall, and 83%F1-score. In contrast, DT, SVM, and RF showed lower performance across all metrics, with ANN proving to be the most reliable for heart disease prediction. The study concludes that ANN offers the highest predictive capability, making it a promising tool for early heart disease detection. Future research could explore the incorporation of additional features, such as lifestyle factors or genetic data, to enhance model accuracy.

Introduction

Mining the massive amounts of healthcare data collected by the industry can reveal previously unknown insights that might inform better decision-making. Heart disease patient mortality rates continue to rise globally, and healthcare providers have access to massive amounts of patient data. Thus, researchers have begun applying data mining techniques to aid in a diagnosis of heart disease[1].

A term "heart disease" encompasses a wide range of medical issues that impact the cardiovascular system and the heart specifically. The signs and symptoms of cardiovascular disease can differ from one kind of disease to another. An issue with the structure or function of the heart as a result of aberrant prenatal cardiac development is known as congenital heart disease. When blood supply to the body's organs is inadequate, a condition known as congestive heart failure sets place [2]. Coronary heart disease, another name for ischaemic heart disease, is the main reason people experience heart difficulties all around the world. Atherosclerosis, in which fatty deposits accumulate inside the blood arteries that provide blood to the heart and subsequently constrict those vessels, reduces blood flow to the heart muscle and is a hallmark of coronary heart disease.

Using clinical data from patients, medical professionals can profit from a system that predicts the likelihood of cardiac disease [3]. Therefore, it is possible to increase a likelihood that patients will be diagnosed with heart disease by creating a system that uses data mining techniques and then undertaking data mining on numerous parameters related to heart disease.

Machine learning allows us to uncover valuable patterns and insights inside them. Among machine learning's numerous applications, illness prediction stands out in the medical industry [4]. Numerous researchers were intrigued by the possibility that ML could enhance the precision, timeliness, and effectiveness of medical diagnosis. Machine learning techniques have many potential applications in medicine, while the focus of this discussion will be on cardiac illness diagnosis. The best way to save lives is to detect heart disease early on, since it is the leading cause of mortality globally[5]. It is right; but post mortem overdiagnosis of cardiovascular disease in unclear cases leads to bias in mortality statistics. The lower diagnostic quality, the higher percentage of ischemic or atherosclerotic heart disease among causes of death [56]

Motivation and Contribution of the Study

The motivation behind this study stems from the growing need to optimise heart disease prediction and early diagnosis using advanced technologies, given the alarming rates of heart-related health issues globally. Traditional diagnostic methods often fall short according to scalability and accuracy, especially when it comes to handling complex and vast datasets that characterise modern healthcare. With the rise of big data in healthcare, it has become crucial to explore innovative approaches that integrate ML and AI to enhance prediction capabilities and outcomes. The following are the primary benefits of this research:

Collection of Cleveland Heart Disease dataset for Heart Disease Prediction in the Healthcare Sector with a focus on accuracy and reliability.

Preprocessing steps, like normalisation, data cleaning, and feature selection, are implemented to ensure data integrity and prepare the dataset for accurate model training.

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Implement and compare Several ML models, including SVM, DT, ANN, and RF, are developed and compared to decide a most effective approach for heart disease classification.

Models are evaluated employing different metrics like F1-score, recall, accuracy, precision, and AUC-ROC to ensure robust and reliable results for early heart disease prediction.

Structure of paper

This paper is organised in the following way: An earlier healthcare study, in the context of diagnosing cardiac disease, is presented in Section II. Methodology, including dataset, preprocessing, and machine learning model details, are detailed in Section III. The experimental results, including an examination of the AI models' performance, are presented in Section IV. Section V wraps up the study and looks at where it might go from here in terms of future research.

Literature Review

This section of the research summarises previous work that has addressed the topic of healthcare-related heart disease prediction through categorisation and detection. Classification methods were the primary emphasis of the literature studied. Some reviews are:

In this study, Karayılan and Kılıç (2017) a backpropagation algorithm for artificial neural networks is suggested as a means of predicting the occurrence of cardiac diseases. With thirteen clinical criteria given into a neural network that was trained using the backpropagation approach, the presence or absence of heart disease could be determined with a 95% accuracy rate [6].

In this research work, Priyanga and Naveen (2018) an analysis is conducted on a smart and efficient system that predicts the occurrence of heart disease using the NB modelling technique. When using a web-based application, users must fill out the necessary fields with the appropriate values. Connecting the dots between the user input value and the trained data, the data is retrieved from a database. While current methods fall short in detecting cardiac illness, this study should help clinicians make better decisions. This approach uses Naïve Bayes for the goal of classifying output data as either very high, low, average, or no heart disease at all. This necessitates the execution of two fundamental tasks: categorisation and prediction. The database and algorithm utilised determine the system's accuracy, which is 86% when using the Naïve Bayes Weighted Approach (NBwa)[7].

This study, Mahboob, Irfan and Ghaffar (2017) focus on a variety of ML techniques that aid in a detection and identification of numerous cardiac disorders. This article discusses a wide variety of ML methods, including SVM, GA, prediction systems, data mining techniques, computational intelligence classifiers, feature selection, and hidden Markov models. They were able to choose the most appropriate method by carefully examining all of them. As a result, they are able to suggest an Ensemble Model that accurately classifies various cardiac illnesses by utilising relevant process learning algorithms. Recent technological developments have allowed for an analysis of a proposed method. Compared to the performance of KNN, ANNs, and SVM algorithms, the proposed method significantly outperforms them with a precision of 0.953, a RMSE of 0.2568, and a ROC of 0.981. Using the ROC, they analysed and evaluated the algorithms that were implemented and the Ensemble Model that was proposed [8].

This study, Singh, Kamra and Singh (2016) is for the purpose of predicting cardiac illnesses. A heart disease forecasting system is developed employing a best results to obtain a prediction accuracy of 99.19% using the hybrid technique for categorisation associative rules (CARs). After put various data mining techniques to a test, the study is implemented using a Cleveland heart disorders dataset by an UCI machine learning library. Gender, age, kind of chest discomfort, blood pressure, blood sugar, and other factors are associated with the causes of cardiac disorders and can be used to forecast the onset of early symptoms cardiac condition[9]. AI technology may improve clinical care, education and training. However, clear regulation and understanding by clinicians are needed. ML is a subfield of AI creating systems that can improve predictions and decisions by exposure to data, thereby imitating human learning [52,53]. ML models in combination with other data iprove prediction quality of coronary artery disease [54]. Problems such as model generalization, bias, transparency, interpretability, accountability, and data privacy remain barriers for broad adoption AI in cardiology [55].

In this study, Ismaeel, Miri and Chourishi (2015) to represent these elements, an ELM framework is employed. An expensive annual physical can be supplanted by the proposed system, which would alert patients to the likely existence of heart disease. The Cleveland Clinic Foundation has acquired the data used to construct the system, which includes information on approximately 300 patients. This architecture has an accuracy rate of approximately 80% in predicting cardiac problems, according to simulation studies [10].

This study, Radhimeenakshi (2016) presents a medical decision-support framework for the rapid, accurate, purposeful, and sane characterisation of cardiac illness. Both the Statlog Database and the Cleveland Heart Database, which are part of the UCI ML dataset vault, were used in this analysis. A proposed system model uses a SVM and an ANN to categorise the data records. Evaluate how well each dataset performed as well [11].

Methodology

The following steps of research design are shown in (Figure 1) flowchart. This flowchart outlines a ML pipeline for heart disease classification using the Cleveland Heart Disease Dataset, comprising 303 instances and 76 attributes, was used, with 14 key attributes selected based on their relevance to heart disease prediction, including age, sex, chest pain type, cholesterol, resting blood pressure, and maximum heart rate. It begins with data preprocessing, including handling missing values, outlier removal, data encoding, and feature scaling. After feature extraction, the data is split into training and testing sets. The splitting ratio is 80:20. Multiple classification models—DT, SVM, RF, and ANN—are trained and evaluated. The outcomes show which model is best for forecasting cardiac problems based on performance measures like F1-score, precision, recall, and accuracy.

Flowchart for Heart Disease Prediction

An overall step of the flowchart for Heart Disease Prediction are provided below:

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Reference	Methodology	Dataset	Performance	Limitation & Future Work
Karayılan and Kılıç (2017)	Artificial Neural Network (Backpropagation)	Clinicalzx records	Accuracy: 95%	Future work could explore other classifiers and additional features.
Priyanga and Naveen (2018)	Naïve Bayes (Weighted Approach)	Healthcare data	Accuracy: 86%	Accuracy depends on database and algorithm; more robust models can be explored.
Mahboob, Irfan, and Ghaffar (2017)	Ensemble Model (Hidden Markov Models, SVM, Genetic Algorithm, etc.) [57]	Heart disease dataset	Accuracy: 94.21%, ROC: 0.981, RMSE: 0.2568, Precision: 0.953	Needs evaluation on more datasets; could explore additional techniques for model improvement.
Singh, Kamra, and Singh (2016)	Hybrid Technique for Classification Associative Rules (CARs)	Cleveland Heart Disease Dataset (UCI)	Accuracy: 99.19%	Improving scalability and expanding testing to other datasets are potential areas for future development.
Ismaeel, Miri, and Chourishi (2015)	Extreme Learning Machine (ELM)	Cleveland Clinic Foundation Dataset	Accuracy: ~80%	Limited accuracy; future work could focus on improving model accuracy and implementing real-time prediction systems.
Radhimeenakshi (2016)	SVM and ANN	Cleveland Heart Database, Statlog Database (UCI)	Not specified	Future work could improve model generalisation and explore hybrid techniques.

Figure 1: Summary of previous study based on Heart Disease Prediction using machine learning techniques

Figure 2: Correlation Matrix of clinical records

Data collection

In this study, use the Cleveland Heart Disease dataset for Heart Disease Prediction in the Healthcare Sector. The current research makes use of data collection that includes 303 instances and 76 attributes in total. Most studies, however, limit themselves to no more than 14 characteristics because of the strong correlation between them and cardiovascular disease. This includes the following features in that order: age, sex, kind of chest pain, resting BP, cholesterol, fasting blood sugar, resting ECG, maximum heart rate, exercise-induced angina, old peak, slope, number of coloured vessels, and thalassaemia. Some of the visualisations are as follows:

(Figure 2) shows that there are a total of fourteen attributes in the dataset, with eight of those being numerical and six being categorical. Characteristics and the values of their aspects. The patient's resting blood pressure is abbreviated as TRESTB PS. FBS is a blood sugar meter. CHOL stands for cholesterol level. The results of resting electrocardiograms are measured using RESTECG. In order to interpret the findings of the resting electrocardiograms, THALACH shows the maximal heart rate of the subject. Exercise-induced angina, or EXANG, is a medical term.

(Figure 3) shows the distribution of predicted values for a model that predicts the sex of a person. The predicted value is shown on the x-axis, while the count of predictions is displays on a y-axis. The number of male forecasts is shown by the blue bars, while the number of female guesses is represented by the green bars. The graph shows that the model predicts more males than females, with the highest number of predictions at the value of 0. The model also makes some

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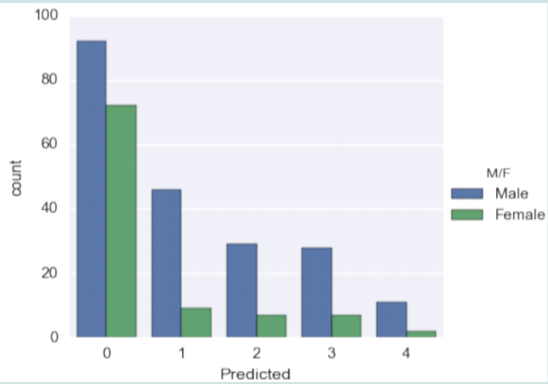

Figure 3: Disease rate in the male and the female.

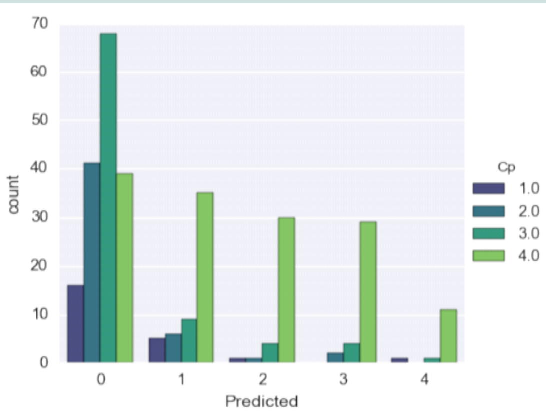

Figure 4: Disease prediction according to chest pain type

predictions for both males and females at the values of 1, 2, and 3, but fewer predictions at the value of 4.

(Figure 4) shows the distribution of the predicted values of a variable (on the x-axis) based on different categories of a categorical variable (on the y-axis). The bars are grouped according to the categories of the categorical variable, which are represented by different colours. The height of each bar represents the count of observations within each group that corresponds to the predicted value on the x-axis.

Data Pre-processing

Processing data is getting it ready to be loaded into the algorithm. Environmental data in its raw form is unfit for processing. Therefore, in order to make it more intelligible, the dataset is pre-processed [12,13]. The suggested solution consists of a few stages, one of which is pre-processing, which involves eliminating null values, empty arrays, and duplicate data. ML models rely on data processing to clean, organise, and organise raw data. The following pre-processing steps are listed below:

Handling missing values

The rows and columns in question will be removed if 75% of the values are lost [14]. Following data deletion, there must not be any introduction of bias.

Remove outliers

Outliers can skew results and lead to inaccurate models[15], so it is crucial to analyse the dataset for these anomalies and remove them to ensure the integrity of the analysis.

Data encoding

After address an ordinality problem, the values of a chest pain kind are encoded into binary values using OneHotEncder. The multi-class dependent variable or value that needs to be predicted is present in this dataset. From zero to four it goes.

Scaling with standard scaler

The Standard Scaler standardises features in the Cleveland Heart Disease Dataset to have a mean0 and a standard deviation1 [16, 17]. This ensures equal contribution to model performance, improving prediction accuracy and can be easily implemented with Scikit-learn. The following equation of (1)

Feature Extraction

After preprocessing Feature extraction is the act of reducing the immense amount of raw data to a more manageable one that is more indicative of the real signal of interest, and that performs more easily for analysis and model performance by isolating and selecting for the most pertinent information [18]. It Condenses the data dimensionality, remove redundancy and picks out important patterns or relationships specifically relevant for the task.

Data Splitting

There was a 20% testing set and an 80% training set within the dataset. The models were optimised and trained on the training set, and their performance was assessed on the testing set. The test set performance of each model was recorded.

Prediction with ANN model

An artificial neural network (ANN) consists of three layers: input, hidden, and output[19]. The neural network receives features through the input layer. When the hidden layer updates the weights, it improves the network's performance. Finally, the output layer gives the network's results in terms of classes [20]. The propagation function and learning rule determine the output of a neural network [17]. The propagation function, which influences the inputs to the j-thneurone by the outputs of the preceding neurones, is expressed in Equation.

where $pj\ (t)$ is a propagation function, $Oi\ (t)$ represents the neuron's previous output, wij is a weight and b is bias.

The learning rule modifies the neural network's parameters to provide an acceptable output for every input set. By modifying the network's weights, the learning process enhances output computation in accordance with the learning rule.

Massive training and back-propagation of mistakes allow the artificial neural network's weights to be fine-tuned, resulting in a faster learning rate [21]. Neural networks excel in interpreting the results of uncertain data sets without prior knowledge of the data sets' evenness.

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Performance Matrix

Several evaluation measures are used to analyse the performance of models that forecast cardiac disease; this completes the picture of how effective the models are [22]. The confusion matrix is used to create the assessment metrics in this study, which comprise F1-score, recall, accuracy, and precision. Here are a component that a confusion matrix breaks down:

True Positive (TP): The model accurately detects cardiac illness when it really exists in the patient.

True Negative (TN): When a patient does not actually have cardiac disease, a model correctly identifies that fact.

False Positive (FP): When a patient does not actually have cardiac disease, a model wrongly labels them as having it.

False Negative (FN): A patient with heart disease is falsely classified as having no heart disease by the model.

Accuracy

The percentage of cases that are accurately identified, including both true positives and true negatives, relative to the total instances, is known as accuracy. Accuracy is calculated via a following Equation (3):

Precision

The percentage of positively anticipated cases that actually occurred out of all positive instances is called precision. It assesses how well the model can prevent false positives. Precision is calculated using the following Equation (4)

Recall

Recall is a percentage of TP that was accurately forecasted relative to the total number of positives. Here, they check if the model can identify every single positive instance. From Equation (5), recall can be calculated,

F1-Score

To create a single measure that is balanced between Precision and Recall, the F1-Score is calculated as the harmonic mean of the two. It really shines in cases where the dataset is skewed. The following Equation (6):

Classification algorithms are sometimes evaluated using the area under the ROC curve (AUC). Values between 0 and 1 represent the area under the curve, while higher values indicate that the classification algorithm performs better in terms of estimation [29].

Results And Discussion

Several categorisation methods were employed in this investigation, and their results are examined in this section. In order to successfully detect cardiac illness, this study utilised AI approaches. The methods like DT [13], SVM [23], RF [24], and ANN are trained on the Cleveland Heart Disease Dataset and assessed employing a performance matrix like f1-score, recall, accuracy, and precision. Table I shows how well the suggested ANN model worked, while (Table II) shows the outcomes of the model comparison.

Table 1

Performance Matrix	Artificial Neural Network (ANN)
Accuracy	86
Precision	86
Recall	84
F1-score	83

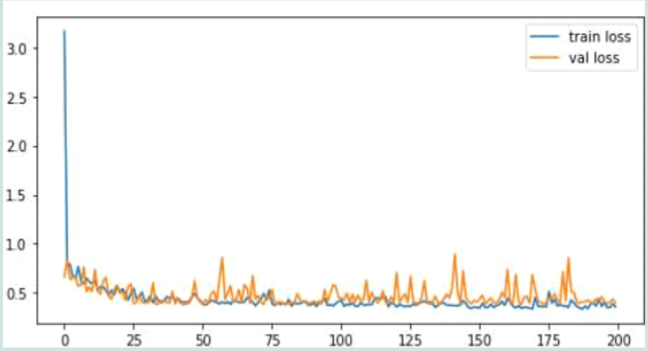

Figure 5: Performance of Artificial Neural Network

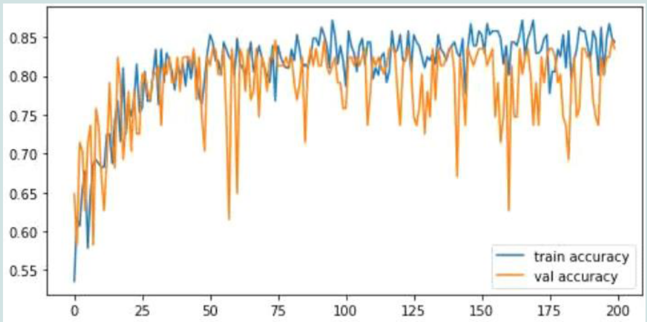

Figure 6: Training and Testing Loss for ANN model.

Findings ANN model performance on Heart Disease Prediction on Cleveland Heart Disease Dataset

(Figure 5) displays a performance of an ANN. A bar chart displays the f1-score, recall, accuracy, and precision of the model. A model achieves an accuracy86%, a precision86%, a recall84% and an F1-score83%. This displays that the model is performing well, with all metrics being above 80%.

(Figure 6) shows the training and validation loss plot illustrating the learning dynamics of the model over 200 epochs, showing a rapid initial decrease in both losses, indicating effective early learning. While the training loss stabilises at a low level, the validation loss exhibits notable fluctuations, likely due to overfitting as the model starts capturing noise in the training data. This is evident in instances where the validation loss surpasses the training loss, highlighting challenges in generalisation.

(Figure 7) shows the training and validation accuracy plot, which shows how the model learnt and how well it could generalise over 200 epochs. Initially, both accuracies show a steady improvement, reflecting effective learning. Around epoch 50, the accuracies stabilise, with both fluctuating between 80% and 85%. The model appears to

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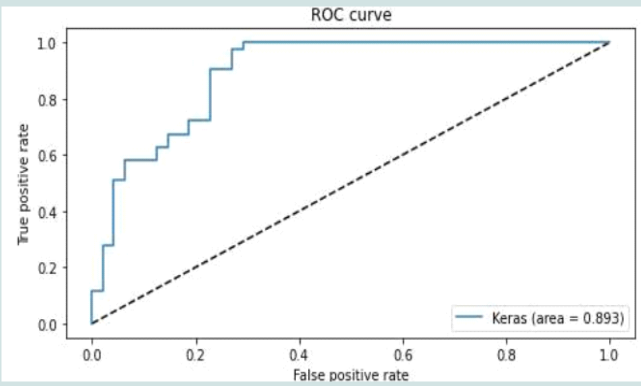

Figure 7: Training and Testing Accuracy for ANN model.

Table 2: Comparative analysis for Heart Disease Prediction between the model's performance

Models	DT	SVM	RF	ANN
Accuracy	77.5	78.1	67	86
Precision	77.4	69.1	64	86
Recall	83.0	42.3	63	84
F1-Score	80.1	-	66	83

have little overfitting, as shown by the tight agreement between the training and validation accuracies, which implies it does a good job of generalising to new data. Despite these fluctuations, the model achieves a reasonably high accuracy, showcasing its effectiveness in addressing the research objectives.

The ROC curve illustrates the model's classification performance, with an AUC of 0.893, indicating strong predictive capability. The curve's steep rise towards the top-left corner reflects high sensitivity at low false positive rates, while its gradual levelling demonstrates robust performance across various thresholds. This excellent AUC result is in line with the research goals since it shows that the model can successfully differentiate between positive and negative classes. The results highlight the model's reliability for the classification task, suggesting its suitability for real-world applications.

The evaluation of model performance, as shown in (Table II), reveals that ANN demonstrated the highest effectiveness with an accuracy86%, precision86%, recall84%, and an F1-score83, making it the most reliable model for heart disease prediction. DT followed closely with balanced metrics, including an accuracy of 77.5%, precision of 77.4%, recall of 83%, and an F1-score of 80.1, indicating consistent performance. SVM achieved a comparable accuracy of 78.1% but struggled with a low recall of 42.3%, resulting in the absence of an F1-score due to its limited ability to identify positive cases effectively. RF, on the other hand, exhibited the lowest performance with an accuracy67%, precision64%, recall63%, and an F1-score66, suggesting significant limitations in its predictive capability. Overall, ANN stands out as the most effective model, excelling across all key performance metrics.

Conclusion and Future Scope

The heart and the arteries that supply blood to it are susceptible to a broad variety of conditions that are grouped together as heart disease. To put it simply, ML algorithms construct models by discovering latent patterns in the submitted dataset. This study employed a variety of datasets, including the Cleveland Heart Disease Dataset, to examine multiple ML approaches to cardiac disease prediction. The primary objective was to assess the efficacy of various classification models, including DT, SVM, RF, and ANN. With an accuracy of 86%, precision of 86%, recall of 84%, and F1-score of 83%, the results show that the ANN model performs better than other methods. This highlights the robustness and reliability of ANN in predicting heart disease, making it a promising tool for early diagnosis in the healthcare sector. To improve an efficiency of ML models, the research also highlighted the significance of preprocessing, which comprises cleaning the data, removing outliers, and selecting features. Accuracy, precision, recall, and F1-score were the metrics used to assess the models, providing a holistic view of how well they performed in practical clinical settings. Improved prediction of cardiac disease may be possible in the future with an employ of modern DL models coupled with real-time monitoring devices.

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