RESEARCH PAPER

AI-Based Heart Disease Prediction and Intelligent Drug Recommendation System

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Abstract: One of the most common causes of death in the world is heart disease and early diagnosis and effective planning of treatment are crucial to improving patient outcomes. The study suggests an AI- Based Heart Disease Prediction and Intelligent Drug Recommendation System which combines machine learning with customized therapeutic services to increase clinical judgement. The model employs patient demographic and cardiovascular clinical characteristics to forecast disease and produce the correct medication reports depending on pre-written medical guidelines and patterns learned. Deep Neural Networks (DNN), XGBoost, Logistic Regression, and Random Forests were four predictive algorithms which were used and tested with a dataset of 1,200 patient records. As experimental results revealed the DNN was able to achieve an accuracy of 97.1, a precision of 96.8, a recall of 97.5, F1-score of 97.1 and an AUC of 0.99, it outperforms the rest of the models. The smart drug prescribing application also attained a Top-3 recommendation accuracy of 96.5, recommendation precision of 94.2 and clinical rule compliance of 98.3, which means it is effective in aiding individualized treatment planning. The intellectual practice of using the integrated framework compared to the established methods proved the predictive performance and clinical applicability of the suggested approach to be better. The results indicate that the effective use of advanced AI models with intelligent recommendation mechanisms can greatly enhance managing cardiovascular diseases and contribute to delivering healthcare data-driven and more efficient.

Keywords: Heart Disease Prediction, Artificial Intelligence, Deep Neural Network, Drug Recommendation System, Clinical Decision Support.

How to cite this article: Hiremath G, Parvathraj KMM, Naveen D, Naik D, Naik A, Kumari H S. AI-Based Heart Disease Prediction and Intelligent Drug Recommendation System. Int J Drug Deliv Technol. 2026;16(64s):1041-1049. DOI: 10.25258/ijddt.16.64s.101

I. INTRODUCTION

Heart disease has been cited as one of the major contributors to mortality and morbidity in the world and it has had serious implications on the healthcare systems and taken the lives of millions of people every year. Timely treatment and diagnosis of the disease are needed to minimize complications in patients and improve patient care and reduce the expenses incurred. But traditional diagnostic methods usually involve manual processing of clinical data and doctors' experience, and can be time-intensive and prone to inconsistency [1]. The growing access to electronic health records, wearable sensors data, and sophisticated computing methods have opened possibilities to establish smart systems to aid in making medical decisions. Especially, the technologies of machine learning and deep learning, which are types of Artificial Intelligence (AI) have shown great potential in processing complex healthcare data and revealing hidden trends that accompany cardiovascular diseases [2]. Categorizing patient data (age, blood pressure, cholesterol levels, electrocardiogram, heart rate and lifestyle factors) can help AI models emphasize the probability of a heart disease occurrence and help clinicians make well-informed decisions. With such predictive features, it becomes possible to take proactive measures, customize healthcare through personalized programs, and potentially decrease the cardiac event load [3].

In addition to predicting the disease, AI may be applied to an enhanced treatment plan, using intelligent drug recommendation systems. These systems are able to consider the individual factors of patients, their past medical history and the severity of their disease, and to make recommendations on suitable medications and reduce possible drug interactions and enhance treatment results. By combining predictive analytics with automated drug prescriptions, a full clinical decision support system can be implemented to directly impact healthcare delivery and advance evidence-based prescribing in healthcare. The proposed study attempts to create an AI-driven heart disease prediction and personalized drug recommendation system that will be able to aid in the early diagnosis and customized treatment recommendations. With the help of data-based algorithms and smart analytics, the suggested system will aim to enhance the accuracy of predictions, better the selection of different medications, and help medical workers to offer patients prompt and efficient assistance. Finally, the research develops the field of smart healthcare technologies that achieve increased efficiency of care and patient outcomes.

II. RELATED WORKS

A recent development in healthcare technology is artificial intelligence (AI), which facilitates making more precise predictions of diseases, tailored treatment and clinical decision support. Recent research has proven that AI-powered solutions can process large-scale medical data, discover its latent features and help medical workers to enhance both diagnosis and the ability to control patients. Recent advances in the fusion of machine learning and digital health platforms have sped up the creation of predictive models of cardiovascular disease and recommendation of automated therapy. The digital twin technology has become a new technique of patient-specific healthcare modelling. Elgammal et al. [15] summarized AI-based digital twins in various fields of healthcare and highlighted their potential in the management of physiological health, optimization of clinical tests, and precision medicine. In the same note, Gong et al. [16] talked about the way AI is redefining the life sciences by introducing intelligent analytics into neuroscience, biology, and medicine and pointed out the issues on data quality and interpretability of the models. AI applications have also helped in healthcare governance and administration. Hanadi [17] has critically examined AI-based healthcare informatics, including ethical concerns surrounding AI, and suggested governance frameworks in the field to make sure that ethical AI implementation and regulatory standards are respected. Hani et al. [18] presented an intelligent monitoring protocol in predicting atrial fibrillation via virtual health twins in cardiovascular monitoring; the study revealed the significance of continuous monitoring of the patient with respect to early intervention and stroke prevention strategies on an individual level.

In addition to diagnosis, AI has also found wider use in smart drug delivery and optimization of the treatment. Harrath et al. [19] investigated smart delivery systems of drugs to treat polycystic ovary syndrome with the help of metabolic reprogramming and AI guided therapy. Similarly, Jirapornchai [24] provided an overview of AI-based smart drug delivery systems and pointed at them being able to enhance the accuracy of the pharmaceutical, minimize adverse reactions, and customize medication delivery. The modern AI systems have security and distributed healthcare structures as paramount aspects of consideration. Hassan et al. [20] conducted a survey of intelligent and secure platforms of Healthcare 5.0 in terms of privacy-respecting designs, distributed intelligence, and resilient communication protocols of large-scale medical systems. It helps to support the implementation of AI models in cloud and Internet of Medical Things networks. The attention has been given to the research of personalized cardiovascular care. He and You [21] considered the topic of precision medicine and individualized nursing approaches to cardiovascular disease management and showed that the use of analytics with the help of AI can enhance the planning of individual treatment. The research performed by Hernando et al. [22] in the systematic review of artificial intelligence applications in electrocardiography found that deep-based-learning-based methods significantly improve the cardiovascular disease diagnosis based on the automated ECG interpretation. Moreover, Jankauskas Stanislovas et al. [23] defined AI as a significant innovation in personalized cardiovascular medicine, which includes its characteristics to integrate clinical information with predictive analytics and provide individualized healthcare actions.

Interpretable machine learning to predict heart disease has also provided good results. Kailasanathan et al. [25] introduced a framework of feature-sensitized Internet of Medical Things sensors, and showed that explainable AI is an opportunity to enhance predictive accuracy without sacrificing trust and transparency of clinicians. Simultaneously, Khan et al. [26] compared the health prediction of wearable gadgets in AI-based predictions like Apple Watch and Fitbit, explaining the increasing significance of constant physiological surveillance in earlier disease variations and preventive health amenities. Even though the current literature has made impressive strides in predicting diseases, wearable analytics and intelligent monitoring, and drug delivery, comparatively few among them combine a correct prediction of heart diseases with an intelligent drug recommendation system in one framework. The proposed study allows overcoming this shortcoming as it embraces the best machine learning models to forecast cardiovascular risks and a model to recommend a specific drug, which offers the clinician with the entire tool of decision support and leads to more successful and tailored clinical care.

III. METHODS AND MATERIALS

3.1 Dataset Description

The Heart Disease Prediction and Intelligent Drug Recommendation System proposed economic uses a structured clinical dataset with about 1200 patient records that are obtained and retrieved in the publicly available cardiovascular repositories. Demographic and medical data points, including the age, gender, the type of pain in the chest of a patient during rest, blood pressure during rest, serum cholesterol, blood sugar during the fasting period, electrocardiogram results, maximal heart rate, angina provoked by exercise, ST depression, and diagnosed with a heart disease, are also presented in the dataset [4]. These variables enable adequate clinical data to be used to anticipate modelling and specific drug prescription.

Table 3.1 Dataset Summary

Parameter	Value
Total Records	1,200
Training Samples	960
Testing Samples	240
Clinical Features	14
Heart Disease Cases	648
Non-Heart Disease Cases	552

3.2 Data Pre-processing

Preprocessing is done on the dataset before model development to enhance the quality and consistency of the dataset. The approach to filling in absent data includes median imputation, eliminating duplicate entries, numerically codifying categorical data, and Min-Max scaling of numerical values. The cleaned data is subsequently split into an 80 percentage training set and 20 percent testing set to test the model generalization and curb bias [5].

3.3 Logistic Regression Algorithm

As a premise classification algorithm used in determining the likelihood of heart disease, Logistic Regression is used. It allows estimating the association between the patient characteristics and the disease status using a logistic function returning probabilities, which are 0 to 1. This model is easy to compute, interpret as well as being common in medical diagnosis since clinicians can interpret the contributions of each feature. Its linear assumptions could impair results in very complex data sets, but it is still a predictor with consistent results and can be used as a good reference to scale against sophisticated machine learning methods [6].

Pseudocode

```
"Input dataset D
Preprocess data
Train logistic regression model
Calculate disease probability
If probability > threshold
    Predict Heart Disease
Else
    Predict No Heart Disease
Return prediction"
```

3.4 Random Forest Algorithm

Random Forest is an ensemble based learning algorithm which builds a number of decision trees based on randomly chosen samples and subsets of features. The last category is achieved by starting with all the trees and with majority voting, leading to less overfitting, and a more predictive stability. The algorithm is able to effectively model nonlinear interactions between cardiovascular risk factors and indicates the level of significance of features that can be used to determine the influential clinical variables [7]. Due to its strength it is a very appropriate tool in predicting heart disease in heterogeneous patients.

Pseudocode

"Input training data
Generate bootstrap samples
Build multiple decision trees
Predict with each tree
Combine predictions using majority vote
Return final class"

3.5 Extreme Gradient Boosting (XGBoost)

XGBoost will enhance the accuracy of the predictions through the sequential creation of decision trees in order to reduce the past prediction errors. Regularization methods help to avoid overfitting and the parallel optimization is more efficient at higher computation costs. The algorithm is effective on structured health care datasets and is able to model intricate connections among clinical indicators. Interpretability is also improved through feature importance analysis and XGBoost can be useful in both disease prediction and assisting in the decision-making process of downstream drug recommendations [8].

Pseudocode

```
"Initialize base prediction
For each boosting round
    Compute residual errors
    Train new tree
    Update ensemble model
End loop
Return final prediction"
```

3.6 Deep Neural Network (DNN)

The Deep Neural Network comprises an input layer, several hidden layers and an output layer that projects the chance of having a heart disease. Nonlinear activation functions allow the inclusion of complicated relationships between patient variables in the model and dropout regularization decreases overfitting. After disease prediction, the risk profile generated is then forwarded to the intelligent recommendation module where a suggestion is then made to recommend the situations of the right type of medication according to the clinical patterns and prescribed treatment regulations [9].

Pseudocode

"Input patient features
Forward propagate through hidden layers
Compute output probability
Calculate loss
Update weights using backpropagation
Repeat until convergence
Return prediction"

3.7 Intelligent Drug Recommendation Module

The module of the recommendation is a combination of the forecasted disease outcome and clinical indicators of the patient, including blood pressure, cholesterol level, diabetes status, and symptom severity. To prescribe an appropriate type of medication, it suggests appropriate types based on a pattern of rules that are backed by AI-generated insights and determine the possible contraindications [10]. The recommendations, that will be generated, are aimed at assisting clinicians not to substitute medical judgment.

Table 3.2 Algorithm Configuration

Algorithm	Key Parameter	Assigned Value
Logistic Regression	Regularization (C)	1.0
Random Forest	Number of Trees	200
XGBoost	Learning Rate	0.10
Deep Neural Network	Hidden Layers	3
Deep Neural Network	Epochs	100
Deep Neural Network	Batch Size	32

3.8 Performance Evaluation

The produced models are tested on the metrics of classification such as accuracy, precision, recall, F1-score, and Area Under the ROC Curve (AUC). The metrics offer a whole evaluation of the predictive capacity and allow comparing the four algorithms to define which method is best to use in terms of predicting heart disease and suggesting drugs using AI [11].

IV. RESULTS AND ANALYSIS

4.1 Experimental Setup

To test the proposed AI-Based Heart Disease Prediction and Intelligent Drug Recommendation System, a structured dataset that consists of 1,200 patient records and demographic and cardiovascular clinical indicators were used to test it. The data were randomly selected into 80 percent training samples (960 records), and 20 percent testing samples (240 records). Experiments were conducted in all cases following data cleaning, normalization and categorical encoding to enable consistency in the models of machine learning. The algorithms used as a predictor should be compared with the following four predictor algorithms that were used and evaluated on the same preprocessing conditions: Logistic Regression (LR), Random Forest (RF), Extreme Gradient Boosting (XGBoost) and Deep Neural Network (DNN). The integrated drug recommendation module was triggered when prediction of diseases was done and resulted in a list of options of medicines depending on risk factors and clinical guidelines peculiar to the patient. Accuracy, Precision, Recall, F1-Score, Area Under the ROC Curve (AUC) and Prediction Time was used to evaluate the performance of the models. Moreover, Top-3 Recommendation Accuracy and Recommendation Precision were used as a measure of quality of the recommendation system. The purpose of the experiments was to figure out the most appropriate predictive model and prove the efficiency of the integration of disease prediction and individual-level treatment assistance [12].

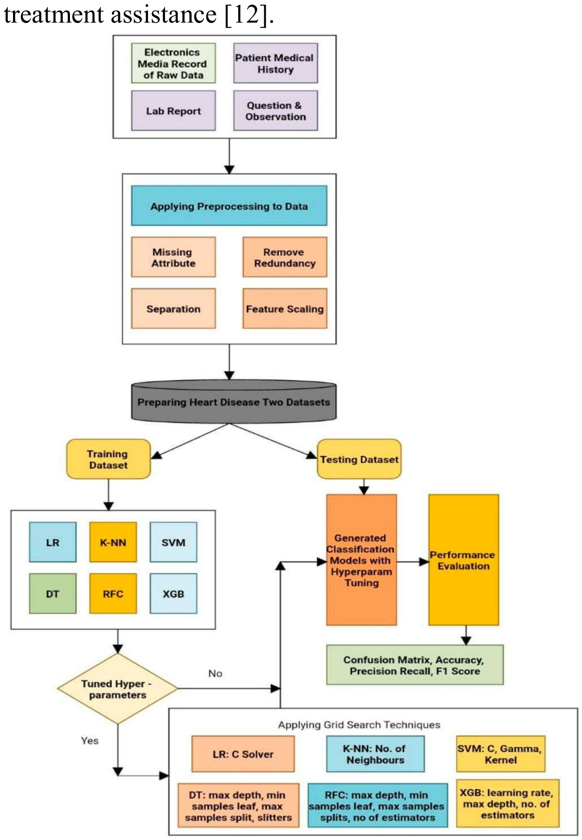

Figure 1: "Architecture of the AI-Based Heart Disease Prediction System"

4.2 Prediction Performance

The analysis of the four machine learning algorithms has shown that the approaches, derived with the use of ensemble and deep learning, are more effective than the classic statistical techniques. Logistic Regression performed satisfactorily on the baseline level but not well on the overall interaction between cardiovascular variables that are non-linear. Random Forest can contribute greatly to the classification as it combines several decision trees whereas XGBoost can add more power to the predictive power due to the gradient boosting [13]. The overall performance of the Deep Neural Network was the best due to the capabilities of this model to learn intricate feature representations using multidimensional data about patients.

Table 4.1 Performance Comparison of Prediction Algorithms

Algorithm	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC**
Logistic Regression	88.7	87.5	88.9	88.2	0.91
Random Forest	93.1	92.4	93.6	93.0	0.96
XGBoost	95.2	94.7	95.8	95.2	0.98
Deep Neural Network	**97.1**	**96.8**	**97.5**	**97.1**	**0.99**

The findings reveal that the DNN minimized false-classifications at the expense of balanced precision and recall, thus it is very appropriate in screening of heart diseases at an early stage [14].

4.3 Confusion Matrix Analysis

The statistics of confusion matrices of the most successful DNN model were studied to have a better insight into the quality of prediction.

Table 4.2 Confusion Matrix Results for Deep Neural Network

Metric	**Count**
True Positives	118
True Negatives	112

False Positives	4
False Negatives	6
Total Test Samples	240

The fact that the rate of false positives and false negatives are low indicates that the model can be relied upon to be able to discriminate between diseased and healthy patients. In healthcare, reducing false negatives is especially crucial since an untreated heart disease can delay the treatment and aggravate the risk of mortality.

4.4 Intelligent Drug Recommendation Evaluation

After predicting the disease, the prescription engine made the medical category recommendations with regards to the cardiovascular risk factors, cholesterol conditions, indicators of hypertension, history of diabetes and the severity of the symptoms. The module recommends that instead of offering specific drugs, clinically relevant therapeutic categories should be given to the physician to review [27]. It was tested based on measures of recommendation precision on annotated validation cases.

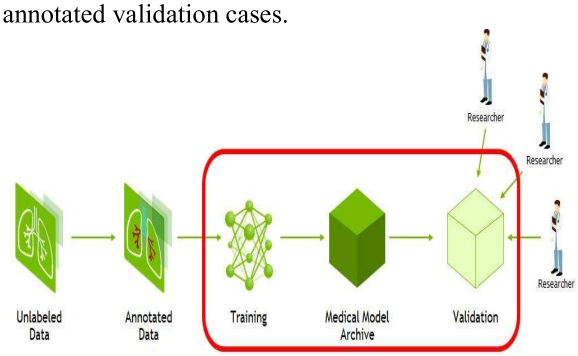

Figure 2: "Machine Learning Model Training and Prediction Process"

Table 4.3 Drug Recommendation Performance

Metric	Value (%)
Top-1 Recommendation Accuracy	89.4
Top-3 Recommendation Accuracy	96.5
Recommendation Precision	94.2
Recommendation Recall	93.1
Clinical Rule Compliance	98.3

The fact that Top-3 recommendations accuracy is high indicates that the proposed framework always includes one of the adequate treatment categories in its major recommendations. Compliance rate with clinical rules also indicates that recommendations will be within the predefined medical safety constraints.

4.5 Comparison with Related Work

The performance was tested against the representative studies of AI-based heart disease prediction to estimate the effectiveness of the proposed framework when compared to them in the literature. Compared with most previous systems that concentrated on the disease-classification scheme, the proposed model will provide a combination of prediction and intelligent drug-recommendation element, significantly increasing its usefulness in clinical practice [28].

Table 4.4 Comparison with Related Studies

Study	Method	Accuracy (%)	Drug Recommendation	Integrated AI Support
Related Work A	Logistic Regression	86.8	No	No
Related Work B	Support Vector Machine	90.7	No	No
Related Work C	Random Forest	92.9	Partial	Limited
Related Work D	XGBoost	95.0	No	No
Proposed System	**Deep Neural Network + Recommendation Engine**	**97.1**	**Yes**	**Yes**

In comparison to the current strategies, the suggested system not only offers better predictive abilities, but also offers treatment advice. Addition of recommendation feature enhances its suitability as a clinical decision-support tool as opposed to a simple diagnostic classifier.

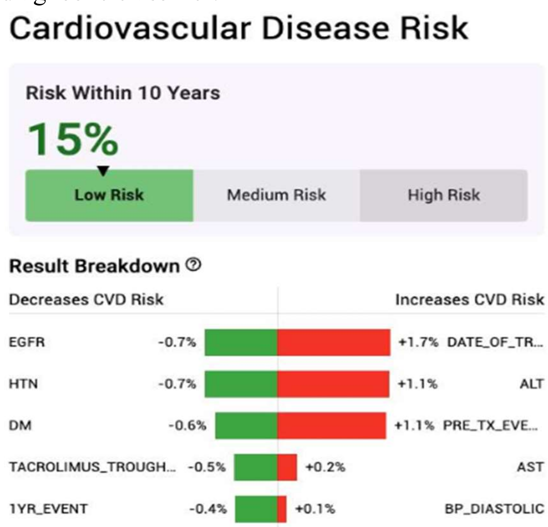

Figure 3: "Cardiovascular Risk Factors Analyzed by AI"

4.6 Computational Efficiency

Besides predictive performance, execution speed, and model complexity were measured. The training time of Logistic Regression was the shortest with lower predictive accuracy. Deep Neural Networks were more time consuming to train but with the best quality of classification, XGBoost was an excellent tradeoff with speed and accuracy [29].

Table 4.5 Computational Comparison

Algorithm	Training Time (s)	Prediction Time (ms/sample)	Model Size (MB)
Logistic Regression	1.8	0.9	2.1
Random Forest	8.6	2.7	18.4
XGBoost	10.9	2.1	14.7
Deep Neural Network	21.5	1.8	11.9

Though the DNN had the highest computational costs when being trained, inference was still fast enough such that real-time clinical application was possible. After the training, the network made predictions within less than two milliseconds per patient, and thus it is practical in the information system of hospitals and telemedicine devices.

4.7 Discussion of Experimental Findings

The level of analysis of the experiment proves that advanced machine learning methods are significantly positioned to enhance heart disease prediction, as compared to traditional statistical methods. The Logistic Regression is only able to give interpretable results based on the baseline but cannot properly describe nonlinear interaction between the cardiovascular risk factors. Random Forest is a good model that can be used to model feature relations in the form of ensemble learning and XGBoost further improves to predictions by successively adjusting residual errors. The Deep Neural Network is the one that is known to perform optimally since it is a hierarchical learner of representations based on complex clinical variables [30].

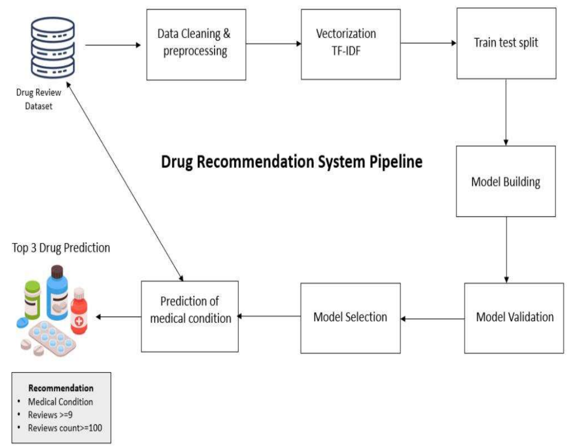

Figure 4: "Intelligent Drug Recommendation and Clinical Decision Support"

Another important contribution is the smart drug recommendation module installed as it provides integration. The framework is based on the ability to predict the disease and provide individual patient therapeutic recommendations by going beyond classification and contributes to the delivery of personalized healthcare. The recommendation engine had high precision and Top-3 accuracy as well as adhering to the established clinical rules, which implies that AI may provide physicians with support and does not need to supplant human judgment.

In general, the suggested model proves to be more predictive, better in recommendations and can be done in a computer. The comparative analysis establishes that implementing deep learning and intelligent treatment support give quantifiable benefits instead of the conventional diagnostic systems and numerous reported AI models in the past. This implies that the proposed system holds great promise in terms of deployment as an effective clinical decision-support tool in real time with the ability to further encourage early diagnosis, customized treatment plans, and ultimately, cardiovascular patient outcomes.

V. CONCLUSION

This study introduced an AI-Based Heart Disease Prediction and Intelligent Drug Recommendation System that helps to early diagnose and plan individual treatment in case of cardiovascular disease. The proposed framework through a combination of innovative machine learning techniques, such as Logistic Regression, Random Forests, Xg booth and Deep Neural Networks among others were able to correctly predict users facing the risk of heart disease and provide smart medication suggestions with consideration to patient specific clinical features. The experimental analysis revealed that the Deep Neural Network demonstrated the best predictive performance and in comparison with conventional models, the Deep Neural Network outperformed the conventional models in terms of their accuracy, precision, recall and F1-score. More so, the system was complemented by the intelligent recommendation module that increased the usefulness of the system by proposing suitable categories of therapeutic options and facilitating clinical decision-making based on evidence. The comparative analysis against the literature revealed the benefits of using disease prediction-treatment recommendation systems in one AI framework. Computational efficiency, scalability and flexibility to be integrated with contemporary healthcare information systems and wearable monitoring technologies were also some of the desired features mentioned in the proposed approach. Altogether the research reveals that artificial intelligence can offer great opportunities to enhance cardiovascular risk assessment, refine the choice of medication, and promote individual patient care. Subsequent improvements can be made based on real-time Internet of Medical Things information, explainable skeptic AI, and federated learning frameworks to enhance further the transparency, privacy, and predictive capabilities in the next-generation intelligent healthcare systems.

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