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A Novel Multi-Level Perceptron for Accurate Heart Stroke Diagnosis

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Abstract

Heart is a very important part of human body, it supply blood to body. If the heart fail down the person cannot survive. This is very important to diagnose the heart disease timely to start proper treatment. To dingoes this disease manually takes time a lot and budget of the patient. Traditionally the patient have to go through form different test then he have to give medical history to the doctor then the doctor make decision about their disease and then the treatment start. In the developing countries especially like Pakistan the income of the people are too much low and they cannot offered different type of expensive tests like ECG etc. In this way the disease cannot detect timely and cannot treated properly. The heart stroke can be predicted by analyzing different attributes like blood pressure, cholesterol age etc., this is a best and easy way to predict heat stroke timely. Different types of Machine Learning and deep learning algorithms are used for heart stroke predictions. In this paper we purposed Novel Multi-Layer-Perceptron (MLP) that are efficient in classification and in heart stoke prediction that model achieve high accuracy of 99%

***Keywords:** Heart disease detection, cardiovascular disease, Classification algorithms, medical imaging*

I. Introduction

Heart disease is fatal diseases across the world that cause a large number of deaths [1]. This is medical condition when heart stop working properly and cannot pump the proper amount of blood to the body parts [2]. The primary symptoms of this disease is chest pain, irregular heartbeat, swollen feet [3]. The current techniques are not much efficient to detect heart disease early so researcher try to find new technologies to overcome these issues and want to detect disease more accurately and timely [4]. This is a big issue of diagnosing the disease timely while using current techniques when the medical expert not available at that time [5]. If the disease can detect timely this is a big chance to treated this and can save the life of patient [6].

There are millions of people that are cause of heart disease are diagnosed yearly [3]. There is also a big strength of people that are stroked by this fatal disease in United states [1]. The tradition diagnosis of heart disease includes collecting the medical history of patient, report of physical health and then all these are analyzed by the medial specialist, but this is too much expensive and time taking process [1]. The patient has to go laboratories to conducting many tests to finding physical reports, this is also a type of burden in form of money to the patient [7]. The heart disease identification is complex task due to tests and other details [8].

In developing countries this is also a big issue for patients to get affordable diagnoses due to low income and other financial issues, the health care equipment's and other health facilities are also limited in these countries [9]. There are four major methods that are used now a days for heart disease diagnosis which include ECG, test of exercise stress, x rays and coronary angiograms [10]. By analyzing different attributes now it is possible to predict the heart store timely these attributes include blood pressure , cholesterol level, age , gender , smoking routine etc. The traditional method for attribute analysis of a patient is time consuming and difficult.

Now a day's Artificial intelligence play an important role in health different machine learning and deep learning algorithms and technologies are now being used to overcome the issues of previous manual methods. In heart stroke prediction it play an important role. By using different machine learning algorithms now researcher make heart disease prediction models that are cheaper and more flexible instead of previous techniques [11], [12], [13]**.** In this prospectus several machine learning approaches using heart disease data sets for training and testing the particular model [14], [15]**,** ,Decision Tree (Al-Qazzaz, Mohammed et al. 2023), Support Vector Machine are introduced by the researchers (Javeed, Rizvi et al. 2020)to predict heart disease . Now by using these models this become very easy to predict heart disease timely. Recent technology off deep learning enhances this field and increase the accuracy [15].

II. Methods

Researchers present eight different type of machine learning models to predict the heart disease. The models that they use for classification are Decision Tree, SVM, XG Boost algorithm, Multinomial Naive Bayes algorithm, Extra Tree algorithm, Logistic Regression, AdaBoost and Linear Discriminant analysis algorithm. There method involves five steps, in step one they get data sets form different online data set collections, and secondly, they process the data by refining and standardization, the third step was hyper parameter tuning to get height accuracy by achieving hyper parameters best value. In step four they apply ML algorithm to classify. In this study the results shows that the accuracy is increased by using standardization of data set, in this study the accuracy of different classifier is improved up to 8.7 percent by standardization the data sets. The overall results Support Vector machine classifier results was best form all other classifier and it attain accuracy of 96.72% [16].

The authors use different ML algorithm to predict heart disease the algorithms include Support vector machine, LR, GBC and KNN. The use Grid Search Cv with these algorithms. They use datasets form different source include Beach V UCI Kaggle etc. The results of the study shows that the extreme Gradient Boosting Algorithm along with Grid search CV provide a best accuracy for both testing and training. The testing and training results was very good 100% and 99%. The study also highlights that Using of optimal hyper parameter can enhance the performance of the algorithms [17].

This paper present different type of machine learning algorithms with feature selection algorithm to predict the heart disease. The algorithms that are used are KNN, Support Vector Machine, LD, GBC RF and DT, the algorithm that are used for feature selection is sequential feature selection.

The results of the study shows that the Random Forest and decision tree provide more accurate results then others the results were respectively 100% and 99%. The study also illustrates that by using feature selection technique the accuracy of algorithms can be enhance [18].

In this research paper the researcher combines two different types of algorithms to propose a model for prediction of heart disease, the algorithms that they combine is Random-Forest & SVM. The main objective to combine these algorithms was to eliminate the iterative feature for selecting the features for the disease. This was done to increase the accuracy of SVM algorithm for diseases prediction. The results of this research show that the hybrid model that they purpose gave more accuracy than the accuracy of individual algorithm Support Vector Machine and Random Forest [19].

In this research the researcher uses different machine learning techniques to predict heart disease, they use K-Nearest Neighbor, RF, SVM and Multi-layer Perceptron to attain their objective of predicting heart disease. The use different type of techniques such as evaluators of attribute, feature elimination and outlier removal to increase the overall performance of these algorithms. They use data sets for this purpose from different sources like Cleveland, Long Beach V and UCI Kaggle for their model. The result of the heart disease prediction of this model was 82.47 to 100 percent [20].

The author presents a new hybrid approach to predict heart disease timely. They combine random forest and support vector machine for this purpose. They apply different techniques to risk factors. The researcher developer there model by using Jupyter Notebook online.The overall accuracy of this model show that the Random Forest classifier gave more accurate result then other algorithms [21].

This research article purpose SCA_KNN (Sine Cosine Weighted K-Nearest Neighbour) ML algorithm to detect the heart disease in the patients. The model learns from the data that are stored in the block-chain. They use block-chain to ensure the integrity of the data of the patients. The results of the study shows that this purposed model gave more accuracy than the W K-NN & KNN. The researcher also compares this algorithm with other algorithm in many ways like precision, mean square error. F1 score etc. This purposed algorithm and the storage system that they describe in their research have a good effect on increasing the accuracy of heart disease [22].

This study, the authors investigated five distinct methods (MMC, Random, Adaptive, QUIRE, and AUDI) for deciding which data to include in a multi-label active learning scenario. By selecting the most crucial data points to query for their labels, the goal was to lower the expenses of labeling. To create predictive models for a dataset of heart disease, these selection techniques were paired with a label ranking classifier, and the classifier's hyperparameters were also tuned by using a grid search. Overall, the study's findings point to the effectiveness of the selection approach in enhancing the learning model's accuracy beyond the data at hand when combined with the label ranking model. However, when comparing the models using the F-score, the performance of the selection process was very impressive when utilizing the optimum settings [23].

Table 1. Literature Review

Reference	**Model Name**	**Overall Accuracy**	**Remarks**
(Absar, Das et al. 2022) [24]	Random Forest, AdaBoost, KNN, Decision Tree	RF: 99%, DT: 96%, AB: 100%, KNN: 100%	RF and DT have high accuracy, AB and KNN achieve perfect accuracy, Utilized Streamlit for computer-aided prediction system
(Yilmaz and YAĞIN 2022) [25]	Random Forest, Support Vector Machine, Logistic Regression	RF: Higher Accuracy	Utilized 10-fold repeated cross validation, RF model had higher accuracy and sensitivity
(Qu, Deng et al. 2022)	Explainable Boosting Machine (EBM)	76% AUC	Birth cohort investigation to predict congenital heart defects (CHDs), Utilized ultrasound screening and EBM model
(Özbilgin, Kurnaz et al. 2023) [26]	Support Vector Machine (SVM)	93% Accuracy	Utilized iris analysis and image processing for non-invasive CAD diagnosis, Demonstrated potential for early CAD detection

(Bhatt, Patel et al. 2023) [27]	Multilayer Perceptron, K-Node Clustering	MLP: 87%	Utilized GridSearchCV for model optimization, achieved high accuracy with MLP, Introduced k-node clustering for improved accuracy
(Nandy, Adhikari et al. 2023) [28]	Swarm-ANN Strategy	95.78%	Proposed Swarm-ANN strategy for smart healthcare framework, Achieved high accuracy and outperformed conventional methods
(Manimurugan, Almutairi et al. 2022) [29]	Hybrid Linear Discriminant Analysis, Faster R-CNN	HLDA-MALO: 96.85%, SE-ResNeXt-101: 98.06%	Achieved high accuracy for sensor and echocardiogram classification, Outperformed other models in accuracy
(MAlnajjar and Abu-Naser 2022) [30]	Deep Learning Model	100%	Developed model to identify heart disease symptoms, Utilized Mel-Frequency Cepstrum Coefficient (MFCC) for feature extraction

A. Datasets

Our data originates from a 1988 merger of four distinct datasets: the Long Beach V dataset, the Cleveland dataset, the Hungarian dataset, and the Swiss dataset. This dataset comprises various characteristics, with the "target" property indicating cardiac disease presence—0 for no illness and 1 for disease. The dataset includes vital information such as age, gender, chest pain type (categorized into four values), resting blood pressure, serum cholesterol level (mg/dl), fasting blood sugar status (binary for levels above 120 mg/dl), and resting electrocardiographic results (0, 1, 2). Additional attributes include the maximum heart rate achieved during observation, signs of exercise-induced angina, the slope of the peak exercise ST segment, the number of major vessels colored by fluoroscopy (0 to 3), and thalassemia status (normal, fixed defect, reversible defect).

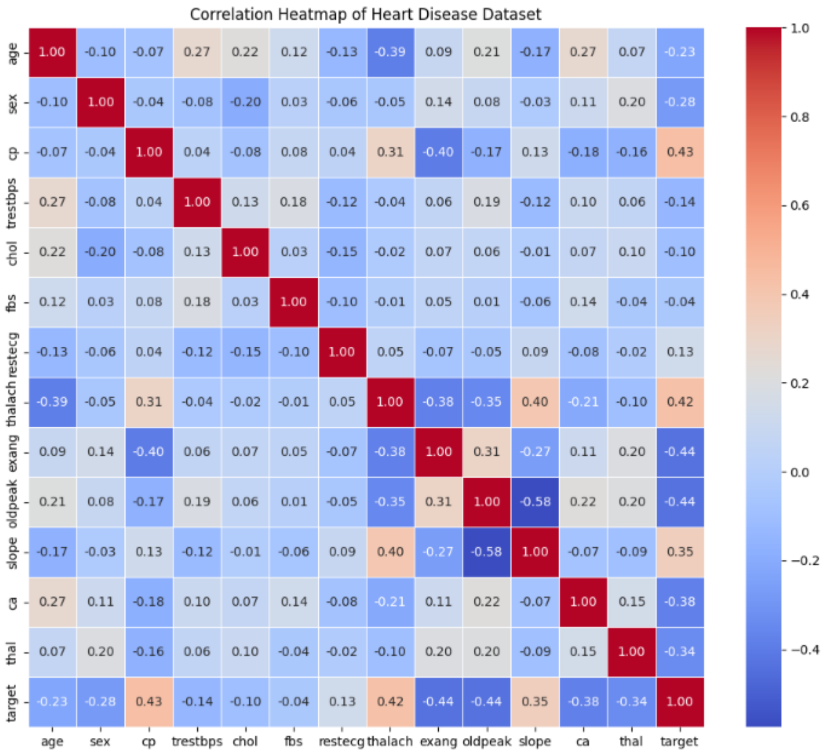

Figure 1. Correlational Heatmap for Heart Stroke Dataset

B. Preparing Data

We first eliminate the missing values to prepare quality and reliable data. We removed six items in the Cleveland dataset due to missing data. So the record reduces from 331 to 297 records. In the following iterations, we focused on shrinking the multiclass values of the predicted attribute, the presence of heart disease, into binary values. For this transformation, we took a value of 0 to indicate the absence of HD and 1 to indicate the presence of HD. We then standardized the data by converting all diagnostic values from 2 to 4 into 1, thus increasing the number of our dataset. In this way, the dataset had the quantity of diagnostic values set to 0 or 1, where 0 meant a lack of HD and 1 meant existence. The two main parts of the data set are characteristics and the target variable for developing our predictive model for heart diseases.

Standard independent variables that can be featured include age, gender, type of chest pain experienced, and other physiology-related parameters. These attributes are given as input to our model so that it can learn and give predictions. But the dependent variable, or target variable, will be the output for which we are trying to make the prediction: whether a patient has heart disease. Decoupling features from the target variables is another essential part of preparing the dataset for training and evaluation with models. This would otherwise be an oversight. It enables us to feed the correct data into our model so that we can test the predictions with accuracy. After normalization and pre-processing, the data set must be divided into training and testing sets. The 80:20 popular approach splits the heart disease data set. Eighty percent of the data is used to train the model, and twenty percent to test the model. By using the training set, data is given to our model for learning from it and the testing data set is applied to test the model for good performance.

C. Multilayer Perceptron (MLP)

Multilayer perceptron is a primary type of artificial neural network, including layers of interacting nodes or neurons. It consists of one input layer, one or various hidden layers, and one output layer. There are built-in capabilities to learn complex patterns in the data and relationships among them. In an MLP, each neuron receives input, performs a linear combination, applies a non-linear activation function, and then passes the results to the next layer. MLPs have been used in nearly all fields of classification and regression as well as pattern recognition problems since they can theoretically approximate any function that contains discontinuities with appropriate data and computational resourcing. In the context of our heart disease prediction, MLPs can learn from these features to classify patterns in the data as a sign of the presence or absence of heart disease.

D. Evaluation Measures

Various Emulation measures were used to determine how much the model could predict heart diseases. These are accuracy, precision, recall, and F1-score.

Accuracy: Percentage of cases that were classified correctly relative to the total number of cases. A model is considered dependable in predicting cardiac problems, and the more accurate it is.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Precision: The Accuracy of the model is measured in terms of how many positive instances have been correctly predicted by the total amount of positive cases. The exact identification of people with heart disease helps avoid many false positives.

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

Recall: Sensitivity, also called recall, measures the ratio of true positives that are successfully anticipated to actual positives. It shows the model's consistency in the wrong detection of heart problems.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

F1-score: It is a metric of evaluation for a model, although its computation involves recall and accuracy. Given that both kinds of wrong outcomes, positive and negative, are taken into account, this would be a good test case for models on imbalanced datasets.

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

III. Results and Discussions

The way toward an adequate heart disease prediction has been marred with searching for such patterns and rigorous evaluation of diverse methodologies. In this work, we tried to take out the mystery of the role of machine-learning methods in the detection of subtle patterns that lead to the presence of heart diseases while focusing on the factors responsible for predictive accuracy and reliability.

Table 2. Contribution Results for thew Heart Stroke Prediction with MLP

	0	1	Macro Avrg	Weighted Avg
Precision	0.97	1.0	0.99	0.99
Recall	1.0	0.97	0.99	0.99
F1 score	0.99	0.99	0.99	0.99
Accuracy	0.99	0.99	0.99	0.99

A. Discussion

We point out key insights gained through our investigation and what these mean for future research and clinical practice. One of the best performers in classification is a Multilayer Perceptron (MLP) model, which achieved an accuracy rate of 99%. The suggested model is strong and dependable, as shown by the assessment metrics for the models used to diagnose heart disease, which consistently show great performance across all measurements. The model was able to get accuracy values between 0.97 and 1.0 across several test sets, to begin with. Nearly all occurrences that were categorised as positive were true, according to precision, which assesses the accuracy of the model's positive predictions. Important in medical diagnostics for avoiding needless treatments or further invasive procedures, this high accuracy implies that the model is very good at reducing false positives.

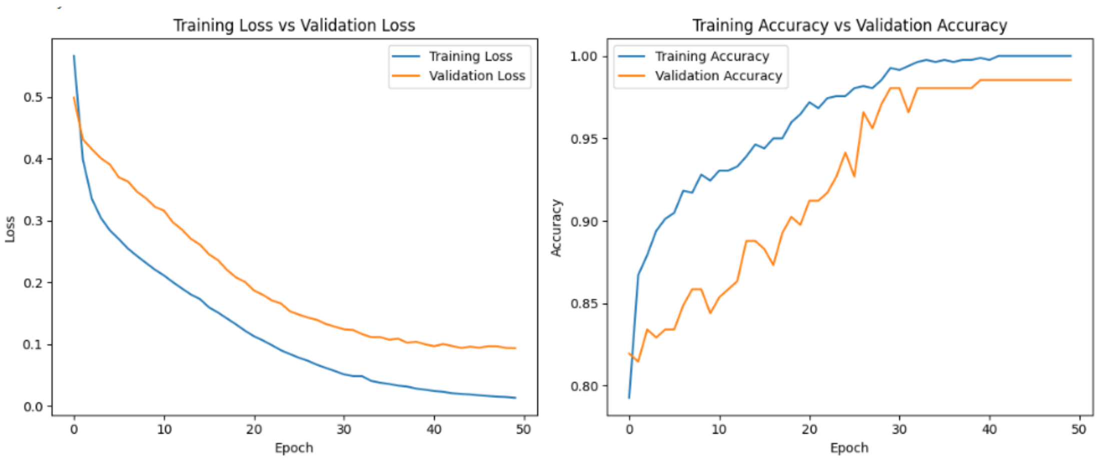

Figure 2. a) Training Loss and Validation Loss is Plotted Over Graph b) Training Accuracy is Plotted against Validation Accuracy

The model's recall values were 1.0 and 0.97. According to recall, which is a measure of the model's accuracy in identifying real positive occurrences, the model does a great job of catching almost all genuine cases of heart disease. To guarantee that no occurrence of the illness goes unnoticed, and that treatment can begin promptly, high recall is especially critical in medical settings. The F1 score, which is a harmonic mean of recall and accuracy, remained constant at 0.99. The model's ability to accurately detect instances of heart disease while also minimising false positives is confirmed by this score, which strikes a balance between recall and precision. The model's balanced performance and its efficacy in sustaining accuracy under varied situations are further shown by the constancy of the F1 score across several test sets.

The model's accuracy was 0.99 across the board, which means that almost all the predictions, positive and negative, were spot on. A high level of accuracy verifies that the model is suitable for practical use in clinical settings by demonstrating its overall dependability in producing accurate predictions. The model's generalizability and robustness are shown by its equal correctness across assessments. These features are necessary for a diagnostic tool that is meant to be used in numerous real-world circumstances. The findings show that the suggested model for diagnosing heart disease is quite effective in terms of accuracy, precision, recall, and F1 score. This impressive performance indicates that the model is not only good at detecting instances of heart disease, but also trustworthy in preventing false positives, guaranteeing thorough and precise diagnoses. Since this is the case, the model may be relied upon by medical practitioners to reliably diagnose cardiac illness. That very high sensitivity level shows the strength of MLP in correctly defining cases of heart disease. Furthermore, MLP has represented good accuracy, precision, recall, and F1-score metrics with the precision of classifying an individual with or without heart disease, which would be remarkable.

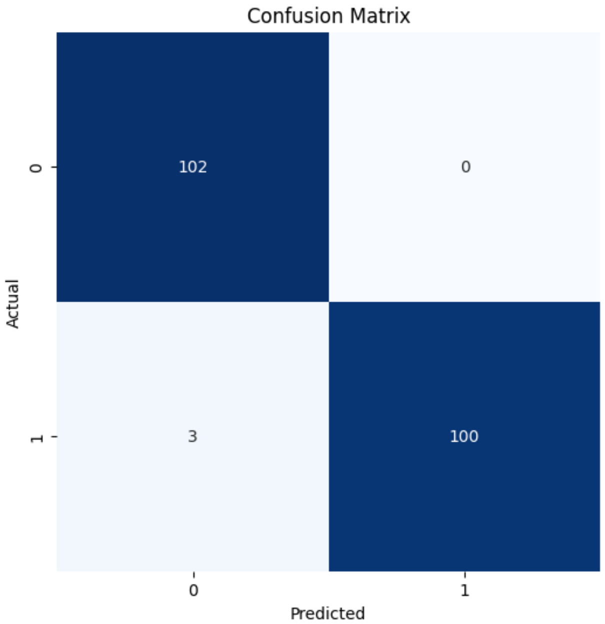

Figure 3. Confusion Matrix

For all the measures, these models showed strong performance, which strengthens the effectiveness of collaborative intelligence in raising predictive accuracy and reliability.

B. Comparative analysis

Recent developments in machine learning and deep learning are shown by the significant discrepancies in accuracy found when comparing different models for the detection of heart disease. In their study [38], found that traditional models like Logistic Regression (LR), K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and a general Deep Learning (DL) approach had accuracies ranging from 83.3% to 94.2%. The Deep Learning model is the most impressive of the bunch, with an accuracy rate of 94.2%. On the other hand, ensemble approaches show that they are more effective. As to the findings of Atallah and Al-Mousa [31], the Hard Voting Ensemble model—which integrates many classifiers—attained a precision of 90.00%. Better forecasts are produced by this strategy since it takes advantage of combining the capabilities of many models.

While the ensemble methods outperform the individual classical models, the Naive Bayes (NB) classifier (84.51 percent accuracy) and the KNN classifier (85 percent accuracy) also perform comparably, according to [32] and [33], respectively. The accuracy of 88.70% achieved by [34] when Decision Tree and Random Forest models were combined shows the effectiveness of ensemble approaches in improving prediction accuracy. Additionally, ANNs have been investigated; however, [35] reported an accuracy of 82.49% using ANNs, suggesting that neural network topologies for the detection of cardiac disease need additional optimisation [36]. demonstrated an accuracy of 88.70% using a linear model and Random Forest, demonstrating the efficacy of hybrid techniques.

According to what [37] stated, one remarkable model, LOFS-ANN (Local Outlier Factor-Support Artificial Neural Network), managed to reach an accuracy level of 90.5%. This methodology improves neural networks' forecasting abilities by using anomaly detection. The suggested model in this research achieves a remarkable 99% accuracy, far surpassing all the preceding models. Significant advancements in model design and training approaches, maybe using state-of-the-art techniques like ConvMixer for effective feature extraction and classification, are indicated by this. All things considered, the comparison study shows how heart disease diagnostic models have progressed, and the suggested model is the most accurate one yet for this vital medical application.

Table 3. Comparison of Contributing results with previous studies

Model	Accuracy	Reference
LR, KNN, SVM, RF, DT, DL	83.3%, 84.8%, 83.2%, 80.3%, 82.3%, 94.2%	(Bharti, Khamparia et al. 2021)
Hard voting ensemble	90.00%	(Atallah and Al-Mousa 2019) [31]
NB	84.51%	(Tougui, Jilbab et al. 2020) [32]
KNN	85.00%	(Pawlovsky 2018) [33]
RF+DT	88.70%	(Kavitha, Gnaneswar et al. 2021) [34]
ANN	82.49%	(Almazroi, Aldhahri et al. 2023) [35]
RF with a linear model	88.70%	(Mohan, Thirumalai et al. 2019) [36]
LOFS-ANN	90.5%	(Goyal 2022) [37]
Proposed Models	99%	Purposed model

IV. Conclusion

In summary, our research represents one giant stride toward realizing the transformational potential of machine learning in predicting heart diseases. We have demonstrated the efficacy of machine learning models for augmenting traditional approaches in heart disease diagnosis and risk assessment through careful experimentation, rigorous evaluation, and nuanced interpretation. We unravelled some novel insights into the complex interplay of factors contributing to heart disease manifestation and progression by applying state-of-the-art methodologies and a multidisciplinary approach. Our results are, therefore, more than a technical tour de force; they also demonstrate the transformational impact machine learning in healthcare can enable for proactive and personalized healthcare interventions. As such, the promise of further increasing predictive accuracy, reliability, and interpretability with continued exploration and innovation in machine learning techniques lies in these critical dimensions: ultimately advancing improved patient outcomes and better clinical decision-making.

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