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HEART DISEASE PREDICTION SYSTEM LEVERAGING MLOPS SITE RELIABILITY ENGINEERING AND CHAOS ENGINEERING FRAMEWORK

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ABSTRACT

This study has proposed automating the predictions of heart diseases using machine learning, with the development of machine learning operations for the expansion of a cloud platform in a very efficient and high-performance way. This work takes principles from Site Reliability Engineering (SRE) to guarantee and cover continuous operational excellence through chaos engineering to test the failing conditions of the system. Prediction of heart disease would mainly depend on high-end techniques like Data Pre-processing, Feature Engineering based on Clustering, Feature Extraction, and SVM Classification. Chaos engineering tests the ability of a system to recover from mistakes in real-life conditions and to give accurate predictions about the faults occurring and their impact. This is to shorten the time between prediction and treatment by diverting prediction to health care practitioners. In this way, healthcare will provide the best care to the patient while ensuring minimal heart disease-related risks. The model achieves an Accuracy of 98.43%, a Precision of 94.24%, a Recall of 95.44%, and a % F1 Score of 97.88%. proving its efficiency in automated heart disease prediction, a powerful monument.

Keywords: Site Reliability Engineering (SRE), Chaos Engineering, Support Vector Machine (SVM), Machine Learning Operations (MLOps).

[1] INTRODUCTION

Heart disease has become the world's leading cause of death, and so stringent detection methods would be needed for prevention. Automating prediction using machine learning for heart disease is a brilliant idea, but this whole thing will become part and parcel of the healthcare system only after a very long journey, which requires necessary contemplations [1]. All these activities are covered under MLOps, which means Machine Learning Operations, involving the deployment of the model, monitoring, and maintenance of deployed models. This MLOps will enable scalability and repeatability of the model engineering process in machine learning [2]. Putting SRE (Site Reliability Engineering) principles on top of MLOps guarantees a better reliability, availability, and scalability of the whole system [3]. According to SRE, it will always keep that system performing at its best post-deployment [4]. A critical operational element of SRE in MLOps would be Chaos Engineering, disrupting the system's availability through fault injection, causing the weaknesses to be exposed [5]. This experiment would help the heart disease prediction systems under real-life issues, such as data corruption or model failure, recover well enough [6]. The collection of MLOps, SRE, and Chaos Engineering makes it unique and at once an impediment to automation in heart disease prediction [7]. The system will always respond to disruption and remain highly reliable, thus giving prediction power to healthcare personnel for timely intervention and better patient care [8]. The reliable forecast automation for heart diseases will collect data usually from sites where heart disease predictions had previously been attempted, and move on to preprocessing that involves various techniques like Missing Value Imputation, One Hot Encoding, and Scaling (Standardization/Min-Max) [10]

Clustering-Based Feature Extraction is part of Feature Engineering, which groups similar data points so that it can extract the patterns that are efficient for the prediction of heart disease events [11]. It would be important to note that a strong classifier like Support Vector Machines or SVM, is very well into the field of work in heart diseases when prediction comes [12]. The rest are tests in the chaos engineering area resilience testing, fault injection, and recovery [13]. Deployment Now continues to the construct of Site Reliability Engineering through continuous maintenance and merging into the daily operations of this system, allowing optimization and dealing with real-world problems hour by hour, in the search for continuous, accurate prediction [14]. Not the least consideration with heart disease prediction is that the application of traditional machine learning algorithms like SVM is an inadequate means of capturing the complex relationships and patterns inherent to high-dimensional health data, which somehow jeopardizes attaining the best possible performance across very large and diverse dataset [15]. Also, feature engineering, most importantly clustering-based feature extraction, might not identify the most relevant features, thereby adverse influence on the accuracy of the prediction model itself [16]. In this respect, preprocessing, which involves imputation and one-hot encoding of missing values, on the contrary, might have, or might not have, introduced bias toward solving the problem, particularly in instances characterized by many missing values or categorical variables with many levels [17]. The other complexity involving the system-wide integration of SRE practices during the deployment phase may also come from the demand for tireless monitoring, which is resource-intensive and laden with operational overhead [18]. A further overriding problem tying this framework is that there hasn't been explicit thought given to model interpretability, a feature that would have ensured acceptance and trust from the medical professionals while limiting its utilization in the clinical environment [19]. Once the system is applied in larger healthcare frameworks with more complex datasets, it will raise problems of scalability, whereas adaptive learning will depend on retraining and updating so that the model adjusts to changes introduced by new patterns of data and new factors related to health [20]. Further concerns arise from the increasing complexity of data preprocessing and the necessity for advanced feature extraction techniques to improve prediction accuracy [21]. Incorporating real-time data feeds may also pose additional challenges for maintaining the accuracy and consistency of heart disease predictions in dynamic environments [22]. Additionally, the integration of adaptive learning methods would require regular updates to the system, ensuring that it stays relevant to emerging healthcare trends and data sources [23]. As the model adapts, there is a risk of overfitting to recent trends, which may compromise the generalizability of predictions [24]. Finally, the computational cost and resource consumption associated with these adaptive learning models and continuous monitoring could become a significant barrier in large-scale healthcare applications [25].

MLOps (Machine Learning Operations) is a set of practices that combines machine learning (ML) and DevOps to automate and streamline the end-to-end lifecycle of machine learning models, from development to deployment and monitoring [26]. It focuses on the integration of ML workflows into production environments, ensuring that models are efficiently managed, monitored, and continuously improved over time [27]. MLOps bridges the gap between data scientists and operations teams, allowing for faster and more reliable deployment of machine learning models [28]. Key aspects of MLOps include version control for datasets and models, automated testing, continuous integration/continuous deployment (CI/CD) pipelines, and monitoring of model performance in real-world environments [29]. By promoting collaboration, scalability, and reproducibility, MLOps enables organizations to manage the complexities of machine learning at scale and ensure that models remain accurate and relevant as they are updated and retrained with new data [30]. The contribution of the paper is below:

- It is a state-of-the-art automated system for predicting heart disease by machine learning algorithms like SVM, which guarantees high accuracy and reliability.
- The paper thus integrates MLOps and SRE principles that allow the system to auto-scale, be reliable, and continue functioning without performance impairment.
- This paper is based on practicing Chaos Engineering to perform real disruption simulations and then check the resilience of this system throughout various conditions.

2. LITERATURE SURVEY

It is proposed to combine all aspects of productionizing machine learning models to form a deployment workflow: implementation of continuous integration, continuous delivery, continuous training, and monitoring, explainability, and sustainability [31]. The methods validated in different application domains ensure business objectives of availability, reliability, and efficiency are attained [32]. Such is the systematic and transparent mode of deploying machine learning models into a real environment in an environmentally sustainable manner [33]. The thesis, in more respects than one, is largely about some very complicated IT systems in regards to AI in Site Reliability Engineering [34]. For the study implementation, extensive reading of the literature and interviews that were qualitative, exploratory, with seven SRE professionals had to be done [35]. It is established through the findings of this study that the new lad on the block to IT Operations will have to go through somewhat of a somewhat growing-up cycle in its maturity [36]. AIOps is said to offer opportunities such as event correlation, noise reduction, and active processes beyond reactive processes [37]. None of these foundations-common data set, centralized architecture, and proactive senior management-will ever see any realization without such implementations [38]. With all said, cross-functional roles are sure to be prioritized, but the SRE team will remain relevant in the foreseeable future [39]. AIOps, depending on the organizations in question, will be one of the major enablers in such teams' maturation [40].

3. PROBLEM STATEMENT

The predictive model has to be subjected to an extensive amount of reliable scaling and robustness testing before putting it into practice [41]. Diagnosing heart diseases is an extremely arduous and painstaking manual operation, and very often, these hours, when spared to intervene in meaningful medical decisions, are filled with errors [42]. The requirement for predictive systems that can be automated and handle huge volumes of health-related data that can be forecasted at the right time is becoming dire [43]. Therefore, the above-explained work shall focus on heart disease prediction with the aid of yet another prediction algorithm-classifier, support vector machine (SVM) [44]. There is a delicate pre-processing step, and the feature engineering is done before this [45]. Reliability in any predictive model is rooted in the performance variations over different datasets; that is what makes it MLOps and SRE compliant [46]. This principle thus triggers the continuous invocation of monitoring, scale-up, and fail-over features in the life cycle [47]. Besides, the chaos engineering notion would be employed to test that system's resilience against artificially inflicted disturbances [48]. This offers an extra layer of protection toward reliable predictions under the worst of circumstances because it ensures system stability through failures, followed by swift recovery afterward [49]. The health checks and verifications during predictions in production settings will be provided through SRE [50]. By further incorporating modern ideas into heart disease prediction, the overall accuracy and reliability of predictions concerning heart diseases shall increase. In this way, enhanced prediction reliability would thereby contribute to the overall patient outcome with adverse risk factors through adoption.

4. PROPOSED METHODOLOGY

The procedure, as indicated in the diagram, starts from Data Collection, which collects data from the Heart Disease Prediction dataset. This dataset contains the critical details of the candidates for whom the heart disease could be predicted. After collecting data, the next stage is Data Pre-processing where the major steps of Missing Value Imputation, which fixes the missing entries in the dataset; One-Hot Encoding, which changes nominal categorical attributes into numbers; and Scaling (Standardization/Min-Max), which normalizes the numerical data and makes it possible for all features to affect the model's predictions equally. Once data pre-processing is complete, the next step is the application of Feature Engineering, wherein Clustering-Based Feature Extraction is used to associate similar data points together to apply meaningful features for prediction model improvement concerning the patterns they display. Then, the prediction of heart disease is done by the Support Vector Machine. SVM is a very powerful machine learning algorithm capable of performing classification tasks, as applied in this case for predicting the occurrence of heart disease in a person based on the features engineered. After modelling and making predictions, Chaos Engineering is applied, which includes Resilience Testing, Fault Injection, and Recovery procedures to simulate failure to enable the testing of robustness in real-world conditions. The next step is to transfer the model to the Deployment phase, that is, to couple it onto a Site Reliability Engineering (SRE) framework. Once the model is deployed, it will be under an ongoing maintenance process to make sure it operates optimally and reliably under actual use, with a mechanism for system health monitoring and eventual troubleshooting of any issues arising.

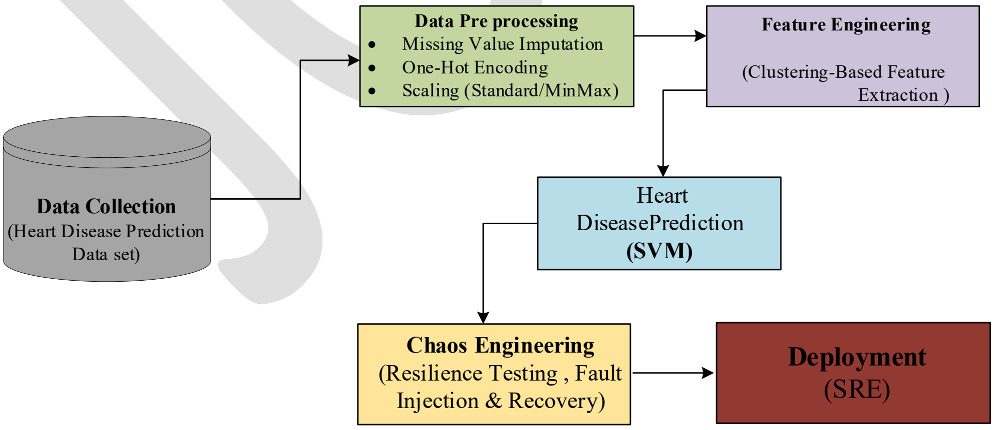

Figure 1: Overall architecture of the proposed method

4.1 DATA COLLECTION

Heart disease prediction is initiated once data is collected. The gathered data include heart disease prediction datasets with necessary features from the individual in predicting whether the person will develop heart disease or not. Some of these features are health attributes like age, sex, levels of cholesterol, blood pressure, smoking habits, and other medical aspects raising the chances of developing heart disease. The collection of data is done very well that one can fit the statement that it is the true engine bringing about the success of the entire process, because it qualifies and quantifies the validity for the predictions of the model of machine learning model. The assumption, though, is that it is much beyond compiling a raw dataset; focusing on having a representative population where one's data comes from-in this case, various demographic groups and health conditions, to minimize any predicting bias. This is essential in setting a really firm foundation on which the heart disease prediction system is set.

4.2 DATA PRE-PROCESSING

Due to their primary duties of cleaning, standardization, and preparation of raw data to feed machine learning models, the heart disease predictor pipeline considers these aspects of data pre-processing. In this case, it is in the context of the following places, as referred to in the diagram:

4.2.1 Missing Value Imputation:

Incomplete records seem to be one of the most troublesome problems in modern real data. For example, if incomplete data are not well-managed, they can also produce incomplete models or models with bias. Missing value imputation is complete when it fills or estimates the absent value within the data. Some of the examples include filling in absent data with the averages, means, or modes of the respective column; substituting lost values through predictive techniques using machine learning algorithms or deep learning models (e.g., regression, k-NN); field-level imputation; and field-level imputation. It would rather be in favor of providing accurate generation prediction using incomplete data, full and incomplete data as well as some incorrect predictions, given as a result thereof. The mathematical formula is

$$\text{Mean Imputation} = \frac{1}{N}\sum_{i=1}^{N} x_i \quad \text{where } x_i \neq missing \tag{1}$$

Where N is the number of non-missing values in the feature, x_i For each non-missing data point, the missing values are replaced with the computed mean.

4.2.2 One-Hot Encoding

Hot encoding allows the user to take the categorical variable and convert it into numbers so it can be processed with machine learning algorithms that ask for numerical inputs. Such as gender, smoking status, and disease history (with the values being male/female, smoker/non-smoker, etc.) are turned into individual columns, either having zeros and ones or having zeros and -1. This enables the model to comprehend these particular features in a distinct numerical way, keeping the rare categorical value intact. The mathematical representation for one-hot encoding is

$$x_i = \int_0^1 \begin{matrix} if\ the\ value\ of\ the\ feature\ is\ the\ category\ i \\ otherwise \end{matrix} \tag{2}$$

Where x_i is the binary variable (1 or 0) for category i, the value of the categorical feature is compared with each of the possible categories to assign the binary value.

4.2.3 Scaling (Standardization/Min-Max):

This is especially crucial with scale, which should not allow one trait to gobble up any others because the measure is much larger than the others when indices are measured in different, odd units and across different ranges. Standardization creates mean 0 and standard deviation 1 data, which is very appropriate for using many techniques using SVM. In contrast, Min-Max Scaling revolves around changing the dataset into fixed ranges such as [0,1]; this will work great in distance-based models or when distance metric scales are affecting the model performance.

4.3 SUPPORT VECTOR MACHINE (SVM)

Support Vector Machine is one of the best supervised machine learning classifiers. Among all classifiers for heart disease prediction, SVM is considered one of the best classifiers in the business. This paper investigates the use of SVM for classifying heart disease classes depending on parameters like age, cholesterol, and general health conditions suggested by the dataset. Proposed is an optimal hyperplane that separates both classes of data points with heart disease/no heart disease. The goal of this approach is to maximize the margin, which is defined as the distance from the hyperplane to the closest data point of either class (the so-called support vectors). This would improve the robustness of the model and generalize much better in unseen conditions. Normally, the data is then separated using a linear and non-linear decision boundary, depending on the complexity of the data for non-linear data. SVM would apply different kernel functions, like radial basis function (RBF), to map the input feature space into a higher dimension until it is separable for such cases. This applies particularly to transformed and feature-extracted information created during the feature engineering phase in a sequence prediction for heart disease. The training set that this development uses consists of labelled data-patients-with heart disease and without heart disease, being used to train the model to predict new unlabelled data by learned patterns. Thus, this one is particularly interesting as far as the above classification problems are concerned. SVMs are indeed among the most powerful and widely applicable in this context of high dimensionality. SVMs are capable of such things: generalization even in the face of overtraining, general problems when the number of dimensions outnumbers the number of samples.

4.4 CHAOS ENGINEERING

These chaos engineering principles do have ties to heart disease predictive systems- that is, the disease one is predicting in time. Here, the chaos engineering scenarios would be alongside the modelling and deployment of heart disease prediction. True testing of the system to find heart diseases shall often depend on how well it detects deliberately planted latent defects that replicate, in the least degree, the practical scenarios. The next will take centre stage with a context proving applicable to the subject matter of chaos engineering:

Resilience Testing: Here, several scenarios would be tested against failures; an amount of data can be faulted, some hardware or connectivity would fail, and model failure. Evaluation of these categories would become predictive failure assessment. So, what we are measuring here relates to the stress resilience of the model; Under what stressful circumstances does it perform anymore?

Fault Injection: Means corrupting the original data, dropping the connections here and there, and introducing latency on the network to inject slapdash instances of fault into the service targeted. The tests examine how the model is affected or recovered with different fault injection mechanisms; this is fundamentally a discovery process to delineate the potential weak spots and edge cases that are less likely to be uncovered in the course of standard training and testing.

Recovery: It simply means that if a real failure happens, the system should recover soon, and performance would hardly be affected. It is one thing that a system should verify the recovery from fault injection, whether it was an automatic recovery or human-influenced; it is another thing for the system to verify that the recovery leads back to the normal state. For heart disease prediction, the meaning of recovery would be retraining the model, recovery of the data integrity, or bringing back the components of the system that have failed.

4.5 DEPLOYMENT

Deployment phase time has its model(s) running in regular operation and making a prediction service for the business. The crux of the matter is to facilitate the patient data used for integrating the model, heart disease risk prediction, and insight into healthcare criteria. In principle, the deployment can be cloud-based, server-based, or a combination of both. However, always assured are the availability of the system for continuous use and processing of real-world input data. Since the day the system is deployed, the team has to ensure reliability, scalability, and performance through SRE practices proactively. This is then able to guarantee uptime, availability, and general system stability, both within the firm and when competing with others. Among the major activities to be started and sustained is the establishment and maintenance of SLOs and SLIs that quantify and monitor system performance along with SLAs. Monitoring tools are set up for this purpose and will, hence, monitor the health metrics related to responsiveness and unavailability. When deployment security and compliance provide the basis for a safe working life, any technology for patient data security and privacy is expected to include encryption, various access control technologies, and applicable privacy laws such as HIPAA or GDPR. The security of authentication and authorization will guarantee that sensitive health information will be accessed only by authorized personnel. While deployment tasks run in parallel, there are activities for monitoring and maintaining the system. The measures encompass many performance metrics: prediction accuracy, system latency, continuous

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updating, and retraining of the model in response to new data and trends that emerge as loads increase regarding data to maintain infinite operational efficiency. Thus, every health professional should be able to input new patient details into the system for prediction coordination, which will give actionable insight about heart disease risk factors. Until that time, with accurate and timely predictions enhancing patient care outcomes, the system will henceforth be made reliable, scalable, and secure.

5. DATASET DESCRIPTION

The Heart Disease Prediction Dataset provides a variety of medical files having important health characteristics for predicting the possibility of heart ailments in an individual in general. These features in the dataset include age, sex, type of chest pain, resting blood pressure, serum cholesterol levels, fasting blood sugar, electrocardiographic results, maximum heart rate achieved, exercise-induced angina, old peak depression because of exercise versus rest, the slope of the peak exercise ST segment, number of major vessels colored by fluoroscopy, and thalassemia. All the features are mixed and matched to assess the possible risk for cardiovascular diseases concerning the individual's physical features and test results. The output or dependent variable, which indicates heart disease in the patient, is dichotomous concerning the presence of the heart disease (1) or absence of heart disease (0). All of the entries in the dataset belonging to a unique individual patient consist of categorical and continuous features; the continuous features represent health metrics such as cholesterol levels or heart rates, while the categorical ones are things like presence of chest pain, and whether the individual has a history of fasting blood glucose levels above a specific cutoff. The datasets provide balance in that samples of varying diversity the perfect environment to develop and evaluate the predictive competence of the machine learning model for the risk of heart disease.

Dataset Link: https://www.kaggle.com/datasets/utkarshx27/heart-disease-diagnosis-dataset

6. RESULT AND DISCUSSION

The work is situated on a system configuration consisting of the 12th Gen Intel(R) Core (TM) i5-12400 Processor, 8 GB RAM, and a 64-bit OS based on the x64 processor architecture. The additional system requirements for the work should consist of a minimum of 4 GB RAM (with 8 GB recommended), an OS of at least Windows 7, a fairly modern CPU (Intel i3 or better), and reasonable storage space (100 GB recommended). The implementation work used PyCharm version 3.11.

6.1 Model Performance Metrics

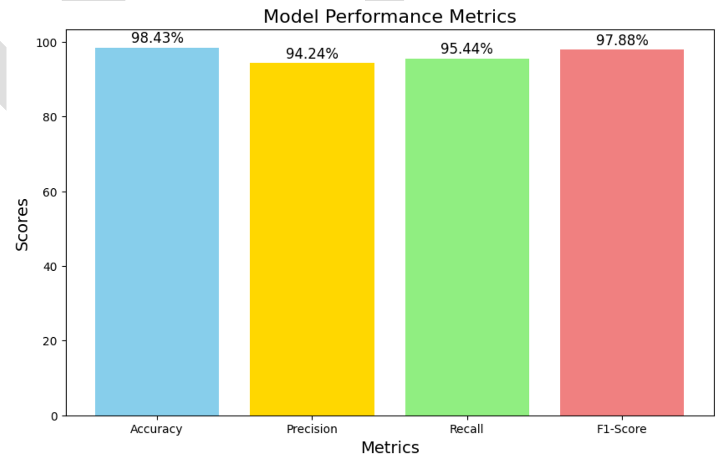

Figure 2: Model performance Metrics

Figure 2 represents the Model Performance Metrics. The four important metrics are accuracy, precision, recall, and F1 score. The accuracy for this model is remarkably high - 98.43%. This illustration means that the model almost always predicts the presence or absence of heart disease properly. It also boasts a precision of as high as 94.24%, thus ensuring the most apt positive predictions. The recall indicates what portion of all people with heart disease would be reported as present: in this case, 95.44%. The F1 score, which is to say the average of both precision and recall, equals 97.88. All in all, the metrics strongly ensure this model's robustness as it proves reliable in predicting heart diseases through model processes translating into action.

6.2 ROC curve

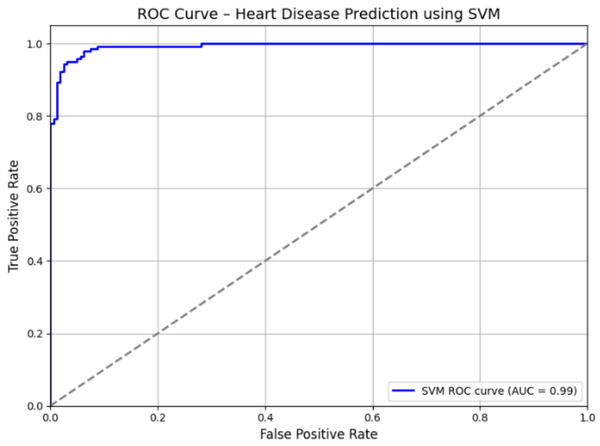

Figure 3: ROC curve

Figure 3 shows the ROC curve. It was used to evaluate the efficacy of the SVM model for assessing heart disease. More; this is a TPR-FPR curve that rises toward the top left corner of the plot, implying that it is an excellent model. It is said to have a high AUC score of 0.99, which implies that the model's performance on differentiation between heart and non-heart disease subjects could be exceptionally high. The dashed diagonal line is that of a random classifier, while the curve of the SVM model is positioned far above it, therefore confirming be very accurate prediction. The strong score in AUC gives the model the probability that it could be a very strong predictor of heart disease.

7. CONCLUSION

MLOps and SRE: Here, they provide the theoretical basis for the proposed heart disease prediction system, thus providing more reliability and scalability in a real healthcare environment. The tenets of chaos engineering give the ability to withstand all possible scenarios of interruptions in the environment, thus providing resilience for the system under various operating conditions. Data preprocessing and feature engineering mean that heart diseases can be predicted using a 98.43% accuracy, 94.24% precision, 95.44% recall, and 97.88% F1 Score with SVM classification. An AUC score of 0.99 was obtained from the ROC curve, and again confirmed its strength and reliability of the model in predicting heart diseases. Hence, any redevelopment of this model toward the prediction of heart disease will ensure better patient outcomes and efficiently facilitate the healthcare system.

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