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Risk Analysis on IoT Health Care Gadgets Using Classification Algorithm

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ABSTRACT

This research presents the development and evaluation of the Modified Coherent Coordination of Data Migration and Computation Techniques (ModCCoDaMiT) framework aimed at enhancing health risk prediction and mitigation within Internet of Things (IoT) healthcare systems. As chronic diseases continue to rise globally, there is an urgent need for effective health monitoring solutions that leverage real-time data from various connected devices, including wearables and medical sensors. The study integrates advanced preprocessing features (Tabu Search) and optimization techniques to analyze heterogeneous health data. Three datasets are considered for training various machine learning algorithms, including Random Forest, Support Vector Machine, and Gradient Boosting algorithm. The study also follows the Extraction, Transformation, and Loading (ETL) process to ensure accurate and timely predictions in addition to the optimized feature extraction using Tabu Search. Performance metrics such as accuracy, precision, recall, and F1-score are utilized to evaluate the effectiveness of the proposed framework. As a result of the comparative analysis conducted, it is shown that the optimized data performs significantly better with a maximum accuracy of 99% in comparison to the health risk prediction model trained with the benchmark dataset.

Keyword: ModCCoDaMiT, ETL, IoT, Framework, Risk Analysis, Healthcare, Gadgets, Algorithms, Patients, Doctors.

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1. INTRODUCTION

Recently, there has been an increase in the total number of patients suffering from chronic diseases, Hypertension and other health issues as a result of unhealthy dietary habits, human emotions, lack of physical activity, alcohol consumption, surrounding environmental conditions and other unhealthy practices. As a result, in order to avert fatal situations, individuals' health status must be observed and examined in their daily lives. Furthermore, the patient must learn monitoring knowledge related to their health condition, which helps healthy life care routines [35]. Software is part of our daily life, present in almost all domains such as education, health, business, and manufacturing. Software engineering is the main discipline in which high quality software is developed by applying user centered design principles. Different tasks and operations of an organization are handled by software systems [18]. Health prediction systems help hospitals promptly reassign outpatients to less congested treatment facilities. They raise the number of patients who receive actual medical attention. A health prediction system addresses the common issue of sudden changes in patient flows in hospitals. The demand for healthcare services in many hospitals is driven by emergency events like ambulance arrivals during natural disasters and motor vehicle accidents, and regular outpatient demand [6].

Furthermore, Medical risk prediction has emerged as a critical component in modern healthcare, particularly with the rise of chronic diseases and the need for timely interventions. The increasing prevalence of conditions such as diabetes, hypertension, and cardiovascular diseases necessitates effective monitoring systems that can analyze patient data in real-time [8]. By leveraging advanced technologies like the Internet of Things (IoT), healthcare providers can collect vast amounts of data from wearable devices and medical sensors. This data can then be analyzed using machine learning algorithms to identify patterns and predict potential health risks, enabling proactive measures to improve patient outcomes. The integration of risk prediction systems within healthcare not only enhances patient monitoring but also optimizes resource allocation in medical facilities, ultimately leading to better healthcare delivery [36].

Feature extraction techniques play a pivotal role in enhancing the performance of machine learning models used for medical risk prediction. Among these techniques, Tabu Search stands out as an effective optimization method for selecting relevant features from high-dimensional datasetsv [33]. By exploring the solution space of feature subsets while avoiding previously visited solutions through a memory structure known as the "tabu list," Tabu Search enables the identification of the most informative features that contribute to model accuracy. This is particularly beneficial in healthcare contexts where datasets are often heterogeneous and complex, comprising various types of data from multiple sources. By refining the feature set, Tabu Search enhances the model's ability to make accurate predictions and reduces computational costs associated with processing irrelevant data [34].

Artificial Intelligence (AI) has revolutionized various sectors, including healthcare, by enabling machines to perform tasks that typically require human intelligence [25]. In the context of medical risk prediction, AI facilitates the analysis of large datasets, allowing for more accurate predictions and personalized treatment plans. Machine learning, a subset of AI, specifically focuses on developing algorithms that can learn from data and improve over time

without explicit programming [7]. This capability is crucial in healthcare, where models must adapt to new information and changing patient conditions.

As AI continues to evolve, its applications in healthcare are expanding, paving the way for innovative solutions that enhance patient care and operational efficiency [47]. Several machine learning algorithms are commonly employed for medical risk prediction, each with its strengths and weaknesses. Random Forest (RF) is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of their predictions for classification tasks. RF is particularly effective in handling large datasets with numerous features and is known for its robustness against overfitting. It also provides insights into feature importance, which can guide further analysis and model refinement [45]. Gradient Boosting (GB) is another powerful technique used in medical risk prediction. This method builds models sequentially, where each new model attempts to correct the errors made by the previous ones. GB is highly flexible and can be adapted to various loss functions, making it suitable for different types of medical data. Its ability to handle complex relationships between features allows for improved predictive performance in risk assessment tasks [37].

Lastly, Support Vector Classification (SVC) is a supervised learning algorithm that finds the optimal hyperplane to separate different classes in a dataset. SVC is particularly effective in high-dimensional spaces and is robust against overfitting when using appropriate kernel functions. In medical risk prediction, SVC can classify patients based on their health indicators effectively, aiding clinicians in making informed decisions about patient care [4]. Moreover, the integration of advanced feature extraction techniques like Tabu Search with robust machine learning algorithms such as Random Forest, Gradient Boosting, and Support Vector Classification enhances the capabilities of medical risk prediction systems. These technologies work together to analyze complex health data efficiently, enabling timely interventions that can significantly improve patient outcomes in an increasingly digital healthcare landscape [1].

Remote monitoring systems in the healthcare domain are increasing the daily reach of health for at-risk populations, especially pregnant women and the elderly. To identify the early disease symptoms and provide care, the patients are monitored every second by using these promising techniques in healthcare. The major functionality of the system is to diagnose and predict the health conditions of the user and provide warnings and training [40] With the help of digitization and digital transformation, the healthcare sector has changed over the past decade around the world. While the use of Machine Learning (ML) algorithms in stratified medicine has its prior footprint in the field. It is also a way to restructure modern health care by providing more individualized and preemptive care, sensing appliances, monitoring on tracking key health indicators such as pulse rate, blood pressure, and electrocardiogram (ECG). [38]

1.1 Statement of the Problem

In IoT-based healthcare systems, there is a growing need to accurately predict and mitigate health risks for patients based on data collected from various connected devices such as wearables, medical sensors, and electronic health records (EHRs) [29]. The challenge lies in developing robust classification algorithms that can effectively analyze heterogeneous and high-dimensional data to identify potential health risks in real-time and implement timely interventions to mitigate them. [14] proposed a Coherent Coordination of Data Migration and Computation platforms (CCoDaMic) framework to mitigate these issues, but comes with certain limitations such as computational cost and lack of an intelligent model to analyze

data risk at the computational level. Hence, this study proposes a Modified CCoDaMiT Approach for risk prediction and mitigation in the domain of health care.

2. RELATED WORKS

In respect to the report of [22], the process includes analyzing the collected data with different machine learning algorithms and sharing the results wirelessly with doctors, who can then make suitable recommendations. The results show that the system allows for real-time remote health monitoring and effectively predicts diseases like heart disease, breast cancer, and diabetes using various machine-learning algorithms. The research problem is the difficulty in providing effective health monitoring to people who do not have access to reliable healthcare systems, even though IoT and networked sensors can improve health information.

According to the research work of [34], Most of the research efforts are now focused on health issues due to the rise in serious diseases and the significance of protecting every human life. The proposed system effectively predicts specific diseases by employing seven supervised machine learning algorithms, thereby improving patient care and emergency response through real-time data analysis. [34] propose a system that leverages machine learning algorithms, IoT, and wireless body sensor networks to facilitate real-time health monitoring and disease prediction using various health sensors.

In respect to the research work of [11] the blending of machine learning algorithms into the Healthcare Internet of Things (H-IoT) is crucial due to the significant amount of healthcare data and the necessity for precise predictions in the fast-evolving healthcare sector. [11] examines several applications of machine learning algorithms in H-IoT, evaluating their effectiveness, benefits, and potential areas for enhancement across various healthcare sectors. This suggest that the uniting of machine learning with H-IoT can greatly improve healthcare delivery and increase the accuracy of predictions related to patient outcomes.

Considering the research work of [6], system attains an accuracy of 98.5% in predicting heart disease, showcasing its superior performance over traditional classifiers by utilizing advanced techniques for feature fusion, selection, and weighting. The accurate prediction of heart disease is crucial for effectively treating cardiac patients before a heart attack occurs, yet existing systems struggle with high-dimensional datasets and lack a smart framework for utilizing diverse data sources. The paper introduces a smart healthcare system designed for heart disease prediction, utilizing ensemble deep learning and feature fusion techniques. This system integrates features from sensor data and electronic medical records, removes irrelevant features, and calculates specific feature weights.

According to the work of [27], a sustainable lung cancer detection model is needed to integrate the Internet of Health Things (IoHT) and computational intelligence while minimizing environmental impact. The model achieved high performance with a specificity of 97.5%, sensitivity of 97.8%, and a mean accuracy of 96.96%, effectively aiding in quick and reliable lung cancer diagnoses A sustainable lung cancer detection model has been created that combines the Internet of Health Things (IoHT) and smart technology to reduce harm to the environment. The model achieves an accuracy of 98.8%, with a specificity of 97.5% and sensitivity of 97.8%, helping doctors make quick and reliable lung cancer diagnoses while saving resources.

According to the research work of [29] accurate and timely disease prediction is needed to support prevention and early treatment, as healthcare seeks to be more proactive instead of reactive. A smart healthcare system has been designed to use data from IoT devices and electronic health records stored in the cloud. It employs predictive analytics with a Bi-LSTM (bidirectional long short-term memory) model to track and predict the risk of heart disease. The system shows strong performance, achieving an accuracy of 98.86%, precision of 98.9%, sensitivity of 98.8%, specificity of 98.89%, and an F-measure of 98.86%, which is better than existing heart disease prediction systems.

3. METHODOLOGY

The section introduces the proposed research framework, thus the Enhanced Coherent Co-ordination of Data Migration and Computation (EnCCoDaMic). The existing framework will be introduced, and the limitation associate with. Additionally, the various system design and illustration will be introduced in this section and this include system framework, and system algorithm.

3.1 System Framework

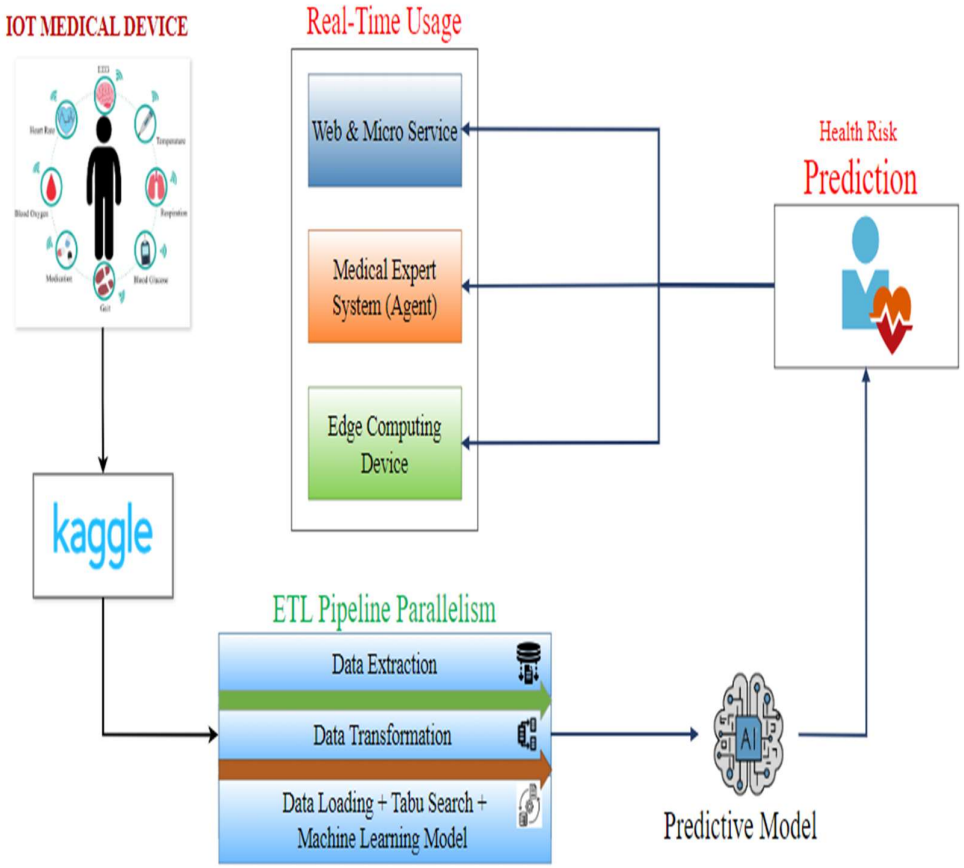

Figure 1: System Architecture

The system architecture is shown in Figure 1, illustrating the proposed framework integral part ranging from the data Extraction, Transformation, and Loading operation which is in parallel operation with Tabu Search feature optimization and model development. The data source considered in this study is of various Internet of Things (IOT) device capable of collecting real-time data related to human health and environment data directly or indirectly affecting human health. The data collected from the heterogeneous IOT devices are Extracted, Transformed, and Loaded in a synchronous manner.

The parallel execution introduces faster, memory-efficient data processing and execution achieved using a python pipeline module. During loading the Tabu Search techniques is introduced to extract highly relevant features, which foster faster data processing via. The loading and Tabu Search all occur synchronously. The process, cleaned and standardized data is finally used for machine learning training. As a result, the health risk prediction model is developed. Lastly, the model can be used in different applications such as for medical expert systems, and in edge computing.

3.2 ETL Pipeline Parallelism

This stage is essential to the modification of the proposed Modified CCoDaMiT (ModCCoDaMiT), the Parallel pipeline is introduced to achieve a single object Transformation, and Loading operation as a single process. At the Transformation stage, the Tabu Search technique is introduced to extract essential features from the dataset, for better machine learning performance. Lastly, the data is use to trained the machine learning model.

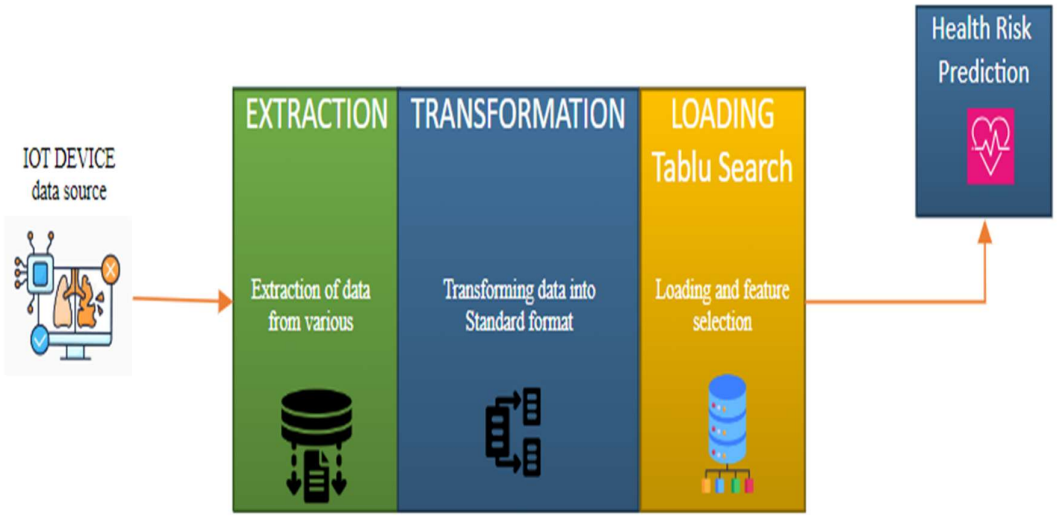

Figure 2: ETL Pipeline

4. RESULTS AND DISCUSSION

Performance Measure

The proposed ModCCoDaMiT Medical Risk and Health Care System will be evaluated based on various performance metrics including accuracy, prediction, recall, and f1-score.

Risk Prediction Health Care Classification Result

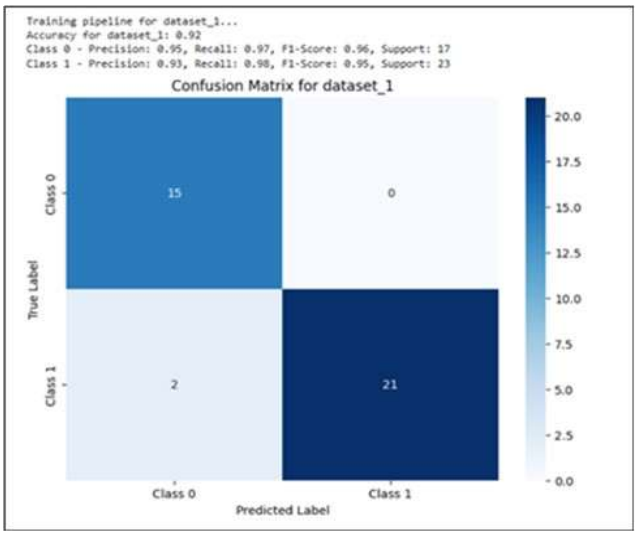

Figure 3: Result Summary on Dataset 1 with Tabu Feature Selection

Figure 3. summarizes the performance of a machine learning model trained on dataset_1 using the optimized Tabu featured selected data version. It shows an overall accuracy of 0.92, indicating high predictive performance. Precision, recall, and F1-scores for each class (0 and 1) are also provided, demonstrating good classification ability. The confusion matrix visually represents the model's predictions, highlighting the number of true positives, true negatives, false positives, and false negatives. Overall, the model appears to be effectively classifying instances in dataset_1.

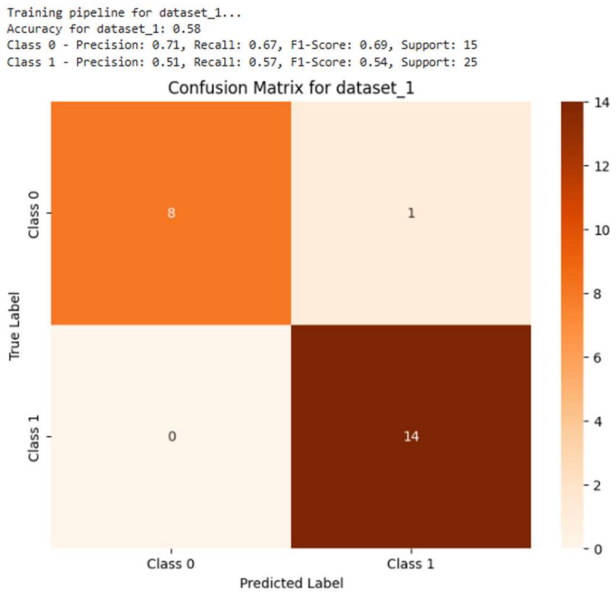

Figure 4: Result Summary on Dataset 1 without Tabu Feature Selection

Figure 4 summarizes the performance of the machine learning model trained on dataset_1 without employing Tabu Search for feature selection. It indicates an overall accuracy of 0.58, reflecting moderate predictive performance. Precision, recall, and F1-scores for each class (0 and 1) are presented, with Class 0 demonstrating better performance than Class 1. The confusion matrix visually depicts the model's predictions, highlighting the counts of true positives, true negatives, false positives, and false negatives. Although the model achieves some level of accuracy, there is significant room for improvement, and the lack of feature selection likely contributes to its lower performance compared to models that utilize Tabu Search.

4.1 Result Comparison with Benchmark Model

Table 1 show the comparative analysis of the benchmark results with the proposed data enhancement using Tabu Search in training the Random Forest, Support Vector Classifier (SVC), and Gradient Boosting models demonstrates a significant improvement in performance metrics. The Random Forest model trained on Dataset 1 achieved an accuracy of 0.69 without feature selection, which increased to 0.92 with Tabu Search, showcasing a remarkable enhancement in predictive capability. Similarly, the SVC on Dataset 2 improved from an accuracy of 0.67 to 0.91, while the Gradient Boosting model on Dataset 3 rose from 0.71 to 0.93. These improvements are reflected across precision, recall, and F1-scores, indicating that the integration of Tabu Search not only optimizes feature selection but also enhances the overall classification performance of the models, allowing them to better distinguish between classes and reduce misclassifications. This underscores the effectiveness of employing advanced feature selection techniques like Tabu Search in boosting machine learning model performance.

Table 1: Result Summary Table

Dataset	Algorithm	Optimized	Accuracy	Precision	Recall	F1-Score
Dataset_1	Random Forest	No	0.69	0.91	0.91	0.91
Dataset_2	Support Vector Machine	No	0.67	0.83	0.76	0.79
Dataset_3	Gradient Boost Algorithm	No	0.71	0.82	0.74	0.76
Dataset 1 + Tabu Feature Search	Random Forest	Yes	0.92	0.94	0.92	0.93
Dataset 2 + Tabu Feature Search	Support Vector Machine	Yes	0.91	0.93	0.92	0.92
Dataset 3 + Tabu Feature Search	Gradient Boost Algorithm	Yes	0.93	0.93	0.93	0.93

5. CONCLUSION

In conclusion, the implementation of advanced feature selection techniques, such as Tabu Search, has demonstrated a substantial impact on the performance of machine learning models, including Random Forest, Support Vector Classifier (SVC), and Gradient Boosting. The comparative analysis revealed significant improvements in accuracy, precision, recall, and

F1-scores across all datasets when Tabu Search was applied, highlighting its effectiveness in optimizing feature selection and enhancing model performance. These findings emphasize the importance of incorporating sophisticated data enhancement methods in machine learning workflows to achieve better predictive capabilities and ultimately drive more accurate decision-making in various applications.

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