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AI-Powered IoMT Framework for Remote Triage and Diagnosis in Telemedicine Applications

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Abstract

Telemedicine is revolutionising health care by enabling remote patient monitoring and diagnosis, which is critical for the management of such chronic diseases as those affecting the heart. Although improved, existing frameworks often focus narrowly on triage or diagnosis, not incorporating multisource data to offer a comprehensive assessment. The proposed AI-powered IoMT-based framework solves these limitations in real-time triaging and diagnosing patients with chronic heart disease. The system integrates sensory and non-sensory information through rule-based algorithms for assigning patients to five emergency categories and offers preliminary diagnosis with practical treatment recommendations. The evaluated system was tested on a dataset of 250 patients in a virtual application scenario, achieving an overall triage classification and diagnostic accuracy of 98.4%. The approach strengthens the capacity of Telemedicine to provide timely, accurate, and resource-effective healthcare, especially in under-resourced or remote settings. Future work will focus on incorporating more advanced AI methods, extending the framework to other chronic diseases, and more considerable real-life scenario validation.

Keywords: Telemedicine, Artificial Intelligence (AI), Real-Time Triage, Rule-based algorithm, IoMT.

I. INTRODUCTION

Healthcare has been a matter of paramount significance since ancient times. Previously, individuals were transported to hospitals for health issues and underwent clinical examinations, diagnoses, and treatments at the medical facility[1]. These processes required considerable time during medical treatments, frequently resulting in the demise of severely ill individuals [2]. Thus, telehealth, specifically telemedicine systems, is presented where patients far from the hospital can be monitored 24/7 in "Remote Monitoring" mode, and the data is sent in real-time to the hospital to provide services. According to the World Health Organization (WHO), Telemedicine refers to utilising information and communication technologies (ICTs) to provide healthcare remotely. The telemedicine system has three layers, as seen in Fig. 1. The initial layer (layer-1) enables users to acquire their vital signs using diminutive, intelligent wireless sensors; the subsequent tier (Tier-2), referred to as the personal gateway or mobile health (mHealth), allows patients to access services via mobile applications or microcontroller programming [3][4][5][6]; Tier 3 is regarded as the healthcare provider within medical institutions. In Tier 3, healthcare providers implement distinctive techniques to deliver sophisticated medical services. The services are returned to the users [7]. Telemedicine allows the exchange of valid information for disease and injury diagnosis, treatment, and prevention [8].

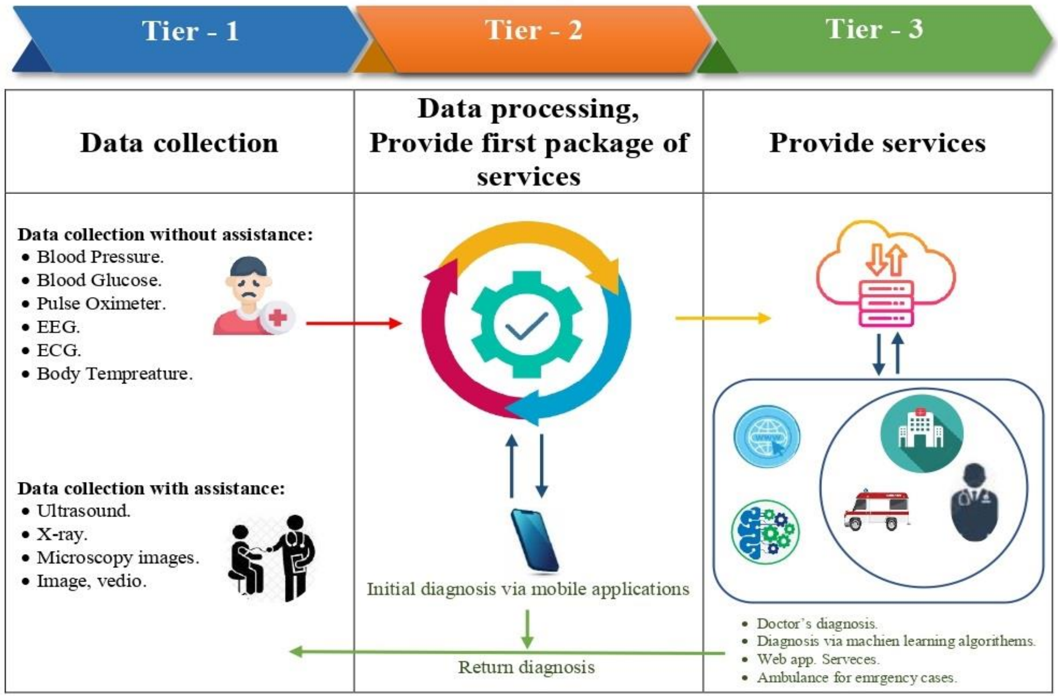

Fig.1: The telemedicine architecture

Telemedicine's primary value is its capacity for remote diagnosis and specialist consultation; when well implemented, it benefits patients, healthcare professionals, and the community [9]. In the future, Telemedicine will play a significant role in patient consultation, health medicine, and several more expanded healthcare uses in isolated rural areas [10][11]. However, the growing number of patients utilising Telemedicine has introduced challenges in managing medical capacity [12]. To address this, remote triage has emerged as a potential solution to accommodate the increasing patient load and ensure the efficient provision of medical services [12]. Remote triage enables patients in remote areas, far from healthcare facilities, to be categorised into one of five emergency levels (Urgent, Risk, Sick, Cold Case, or Normal) based on their condition before reaching the hospital [13][14][15][16]. This approach aims to expedite medical services within hospitals and reduce patient waiting [12]. Despite all its benefits, remote triage in real-time telemedicine applications faces remarkable limitations. Current remote triage models frequently narrowly concentrate on triaging patients' emergency levels, neglecting to provide sufficient information about their medical condition. This is crucial for telemedicine patients who live far from hospitals. This gap is severe for real-time applications, where multiple patients simultaneously require medical services from the same healthcare facility. Currently, most remote triage models rely solely on data from wearable sensors, neglecting other valuable inputs such as EMRs or textual patient data. Such extra data sources are highly relevant for achieving a thorough medical assessment and supporting sound decision-making.

To overcome these limitations, there would be value in taking a step forward in developing remote triage systems by integrating diagnostic abilities into the framework. A combined triage and diagnosis model would offer remote patients a preliminary medical evaluation, empowering them to take immediate and informed action while awaiting hospital services. Such integration could close critical gaps in real-time telemedicine applications and improve outcomes for remote patients. This study aims to address a structured, step-by-step methodology for the remote diagnosis of patients, focusing on those with chronic heart disease. The research outlines a scenario utilising AI-driven IoMT systems to enhance the accuracy and efficiency of initial diagnostic processes in Telemedicine.

II. LITERATURE REVIEW

A. IoT, IoMT, sensors and wearable devices

Wire and wireless body area sensor networks can be used to collect data from patients, such as in [17][18][19][20][21][22][23][6]. In [2], biomedical sensors are used. Sensors can collect patient health attributes and transmit them to doctors for review. In [24], Raspberry Pi sensors are utilised to gather data, including temperature, blood pressure, pulse, and electrocardiogram (ECG). IoT sensors can also Assess an individual's vital signs for data analysis to forecast outcomes, commonly termed 'healthcare sensors with gateway devices.' [25]. IoT devices are also employed for remote monitoring and emergency notification systems [26]. Wearable devices are exploited to collect data, such as belts applied to detect fainting cases or critical situations [4], m-GreenCARDIO embedded systems [27] and wearable sensors [28]. Wearable subsystems to support hands-free teleconsultation, such as smart glasses, are utilised to communicate with specialised personnel [29]. Mixed reality glasses worn by emergency personnel can transmit audio, video, and data streams via a 5G network to medical professionals [30]. Another example is helmets [31]. In [32], Medical equipment integrated with Wi-Fi and other wireless or wired communication technologies enables machine-to-machine communication, serving as the cornerstone of the Internet of Medical Things (IoMT). The Internet of Medical Things (IoMT) idea offers a comprehensive platform for healthcare monitoring through wearable smart devices [33]. In [34], a doctor robot system with a camera and a machine arm equipped with sensors is proposed.

B. A.I. Technology in remote diagnosis

Artificial intelligence (AI) systems may evaluate vital signs, medical histories, and real-time data gathered via wearable technology, such as in [28] used wearable sensors. Smart glasses are used to communicate with specialised personnel [29]. Mixed reality glasses worn by emergency personnel can transmit audio, video, and data streams via a 5G network to medical professionals [30]. Other examples include helmets [31]. On the other hand, telemedicine platforms use sophisticated algorithms and machine learning and, in [35], use a multilayer perceptron neural network. In [36], Using fine KNN, unsupervised learning is utilised. In [24], ML (neural network and fuzzy KNN) algorithms are used. In [18], long short-term memory neural networks are used. In [32], an integrated algorithm allows IoMT applications to utilise knowledge for making automatic decisions. In [28], a J48Graft decision tree (DT) classifier is used. In [37], a bi-directional LSTM is the best technique. All these enable first responders and paramedics to prioritise care, make well-informed decisions on the spot, and even conduct remote consultations with specialists. Artificial intelligence (AI) enhances patient outcomes and optimises resource allocation in emergency care by enabling prompt interventions, resulting in a more efficient healthcare system.

C. Remote Triage Systems and Medical Guidelines

Remote triage systems allow patients to report symptoms and get advice on the appropriate level of care. Frequently before, they visited hospitals. Medical guidelines are crucial because they offer evidence-based frameworks that help medical staff make reasonable judgements concerning patient triage and management. These recommendations can help remote triage systems guarantee that patients receive correct and timely care. This integration of technology and standardised medical practices not only enhances patient safety but also improves overall healthcare efficiency, especially with the spread of chronic diseases [17] and the increasing number of deaths due to CVD [38][24]. In [24], patients were classified as to whether they were infected with cardiovascular disease (CVD). It relied upon Raspberry Pi sensors to collect the data, including temperature, blood pressure, pulse, and electrocardiogram (ECG). In [13], the researchers design and implement a tele-monitoring framework to accurately classify users based on multi-sources data fusion such as (ECG, BP, SPO2 and text inputs, including user location and symptoms. In [39][40], Researchers introduced a methodology for prioritising extensive data on patients with chronic heart illnesses assessed using primary metrics: ECG, SpO2, and BP sensors, in conjunction with non-sensory evaluations such as dyspnea, angina, palpitations, and the patient's status at rest or during exertion. The study [12] introduced a framework called the Triaging and Prioritising Model (TPM), a scalable telemedicine system aimed at enhancing the real-time healthcare monitoring capabilities to address the growing patient demographic suffering from chronic heart disease by minimising wait times for medical attention, prioritising patients with the most critical emergencies, and ensuring timely medical care for all patients based on the same certified medical resources. [40] and [39]. Four vital indicators are used in a research study [41] to examine and describe the different chronic diseases: oxygen saturation (SpO2), blood pressure monitoring, electrocardiogram (ECG), and text frames like that certified in [12][39][40]. Following this, Multi-Criteria Decision Making (MCDM) tools were created to rate and choose patients with Multiple Chronic Conditions (MCCs). A hybrid decision-making and voting method (HDMVM) was presented to assess their crises. The study [42] Developed an emergency categorisation and prioritisation strategy for managing chronic heart disease (CHD) patients in remote health monitoring systems. The framework uses Dempster-Shafer's theory and a hybrid model of MLAHP and TOPSIS to triage patients, and the classification technique relies on ECG sensors, BP sensors, SpO2 sensors, and textual data including shortness of breath, chest discomfort, palpitations, and physical condition.

In [43], A robust home health monitoring system has been developed to assess patients' blood pressure and glucose levels, dispatching categorised notifications to healthcare practitioners upon identifying anomalies. Given the unpredictability of patients' chronic diseases (chronic heart disease, Hypertension, hypotension, and diabetes), blood pressure and glucose are classified as predictors. At the same time, the outcome is recognised as the response variable. In [44], Researchers claimed that the Machine Learning-Based Remote Triage (ML-ART) technique is a foundation for Telemedicine for patients remotely from hospitals. They were utilising the telemedicine system. Telemedicine servers gather and transmit data to categorise each case into five levels. The proposed structure comprises six medical sensors: ECG, SpO2, blood pressure, temperature, respiratory rate, and diabetes sensors. We use additional text inputs to correspond with symptoms such as rest, movement, intense thirst, impaired vision, and urine. In the [15], Researchers propose to handle data from several heterogeneous sources in IoMT-based real-time telemedicine systems, incorporating four medical sensors. The sensors include the electrocardiogram, oxygen saturation, blood pressure, and temperature. Additional symptoms include dyspnoea, thoracic pain, palpitations, left arm discomfort, cephalalgia, and overall physical condition. We employ a model that combines principal component analysis and decision tree approaches to triage patients with the most critical conditions efficiently. We assessed the model utilising a population of 55,680 patients diagnosed with two chronic ailments: cardiovascular disease and Hypertension. The study [16] Implemented the Real-time Triage Optimisation Framework model to improve decision-making in emergency healthcare by enabling real-time prediction of patient severity, utilising an innovative methodology that amalgamates diverse data from the Internet of Medical Things, including sensor data (ECG, Blood Pressure, SpO2, and Temperature) and textual information from electronic medical records, which encompasses patient demographics, lifestyle factors such as smoking status and alcohol consumption, and clinical notes.

TABLE I. TABLE: STATE-OF-THE-ART RESEARCH THAT INVESTIGATED PATIENT TRIAGING SYSTEMS

References	Year	MCDs	Remote monitoring	Increasing the number of patients	Targeted Tier	Mini-time patients wait for services	Number of sensors	Non-sensory data (text)	Number of features	Disease types	Method
[24]	**2019**	□	□	□	**Tier-3**	□	**4**	□	**14**	**Cardiovascular**	**(M2M) technology and ML (KNN)**
[13]	**2014**	□	□	□	**Tier-2 and Tier-3**	□	**3**	□	**11**	**Heart disease**	**MSHA model Data Fusion method and prioritisation technique**
[40]	**2018**	□	□	□	**Tier-3**	□	**3**	□	**11**	**Heart disease**	**MLAHP and TOPSIS**
[39]	**2017**	□	□	□	**Tier-3**	□	**3**	□	**11**	**Heart disease**	**BFAWC and TOPSIS**
[12]	**2020**	□	□	□	**Tier-2 and Tier-3**	□	**3**	□	**11**	**Heart disease**	**TPM model Evidence theory with Fuzzy Cluster Means (FCM)**
[41]	**2020**	□	□	□	**Tier-3**	□	**3**	□	**11**	**Heart disease, High and low blood pressure**	**Hybrid D.M. and voting method (HDMVM)**
[42]	**2022**	□	□	□	**Tier-3**	□	**3**	□	**11**	**Heart disease**	**Dumpster–Shafer and hybrid MLAHP and TOPSIS**
[43]	**2022**	□	□	□	**Tier-2**	□	**2**	□	**9**	**Diabetes is predicted using glucose levels and blood pressure**	**Support vector machine**
[44]	**2023**	□	□	□	**Tier-3**	□	**6**	□	**19**	**Diabetes, Heart disease, High and low blood pressure**	**ML-ART model Machine learning algorithm based on decision tree (D.T.) method**
[15]	**2024**	□	□	□	**Tier-3**	□	**4**	□	**14**	**Heart disease and Hypertension**	**DPTM model Hybrid PCA with ML algorithm**
[16]	**2024**	□	□	□	**Tier-3**	□	**4**	□	**20**	**Heart disease and Hypertension**	**Real-Time Triage Optimization Framework (RTOF) using machine learning**

The research identifies critical gaps in remote triage systems, including limited sensory and non-sensory data integration and a lack of real-time diagnostic capabilities. These limitations hinder timely decision-making and accurate patient assessment. The proposed framework addresses these issues by incorporating a hybrid simultaneous triage and diagnosis model, ensuring improved efficiency and patient outcomes.

III. METHODOLOGY

In Telemedicine, this research proposes a Remote Initial Diagnosis Framework, RIDF, for real-time diagnosis and triage of patients with chronic heart disease. The RIDF framework integrates the Internet of Medical Things with Artificial Intelligence to provide an all-rounded approach toward diagnostics and resource allocation challenges in emergency healthcare scenarios. Figure 2 shows a model of remote primary diagnostics in emergencies, which examines various medical data and provides an accurate preliminary diagnosis and triage. The sequential steps needed to build a similar model for diagnosing multiple medical conditions are shown below. Each step mentioned will be described in detail in the following sections.

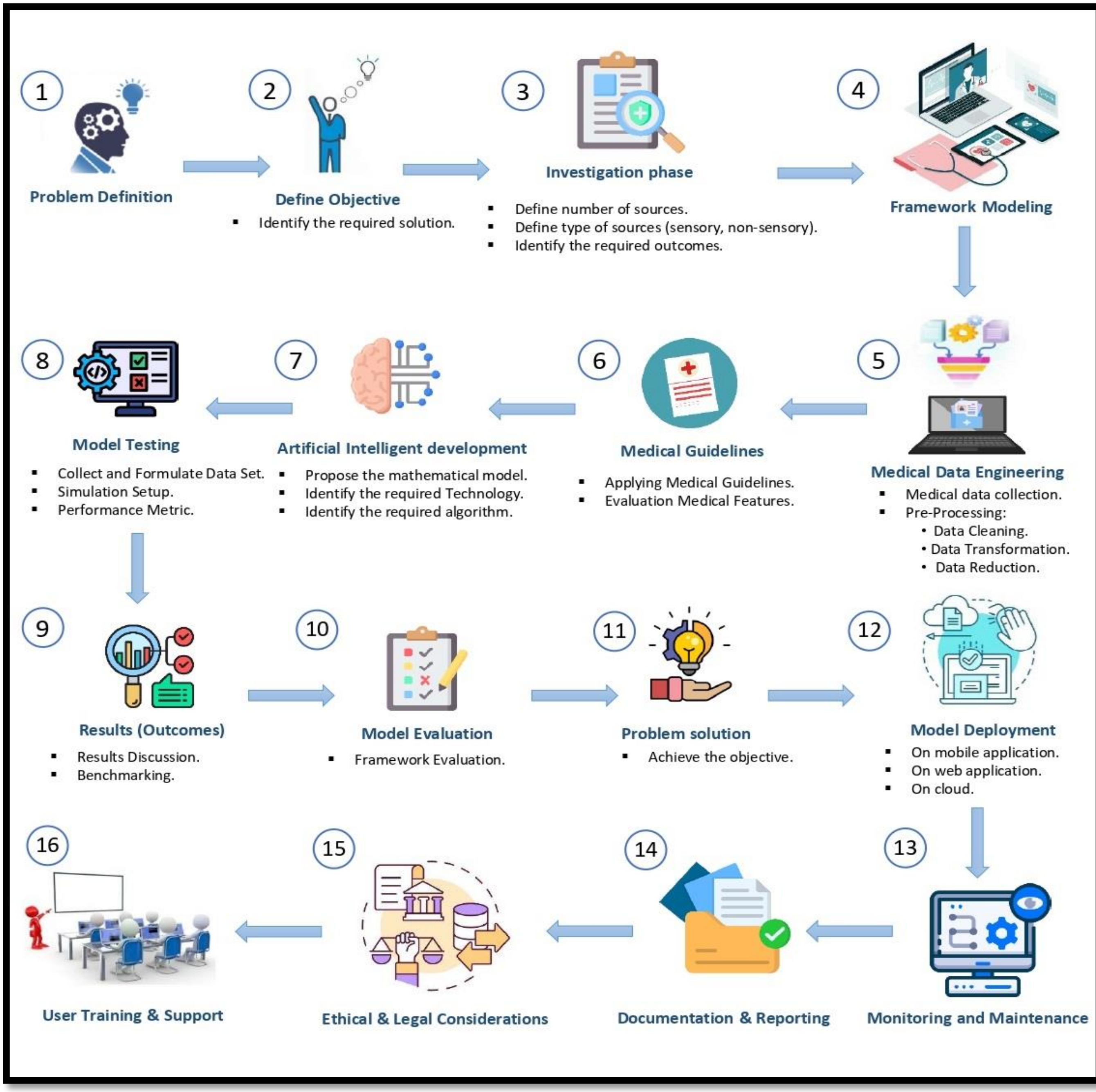

Fig. 2: Proposed Methodology

A. Framework Modeling

The Remote Initial Diagnosis Framework (RIDF) is proposed to fit the solution proposed in the previous paragraph. It consists of three levels. The initial layer (layer-1) is the data collection module, which aggregates data from medical sensors and manual inputs provided by the patient. The second layer (layer-2), the base station, receives all data. Data is checked and cleaned in the base station from values that conflict with previously established standards. Then, these values are entered into a set of rules-based algorithms to obtain the patient's initial diagnosis and triage level. Finally, the results are sent to the hospital in Tier 3. Figure 3 illustrates the three tiers and the overall architecture of the RIDF extension design. This diagram delineates the sequential process flow of the framework, encompassing the data-gathering and server modules.

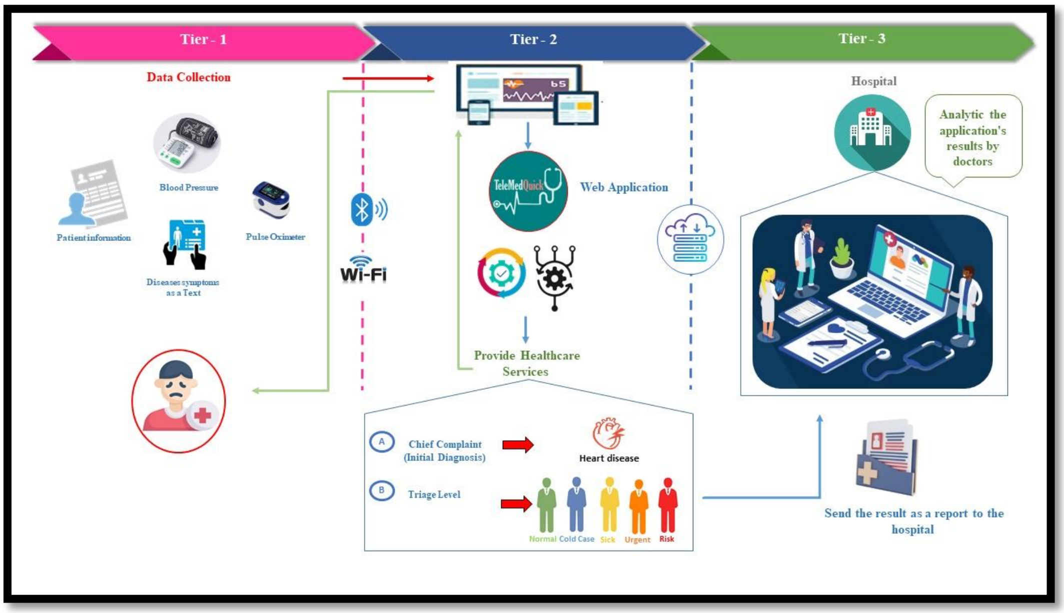

Fig. 3: Proposed Framework

B. Medical Data Engineering

1. Medical Data collection

The patient data are collected from heterogeneous sources, such as non-sensory sensors (text data); this process is done in Tier-1 of Telemedicine. The patient utilises a text frame to convey their symptoms and complaints to the physician. Furthermore, the patient's physical condition will be filled by using our proposed framework, which is equal to making the diagnosis in the form of questions to be answered. Alongside the data obtained from medical sensors (SPO2, blood pressure), The patient/user may substitute the blood pressure sensor with manual medical instruments that assess the corresponding vital signs.

2. Preprocessing data

We performed data cleansing to remove outliers and impute missing values. We utilised mean imputation to address absent values in the patient's reported symptoms and a range-based filter, grounded in medical guidelines explained in Table II, to rectify anomalies in the sensor data, including inappropriate spikes. Textual inputs underwent preprocessing through tokenisation and feature extraction methods to standardise patient responses, as shown in Tables II and III.

TABLE II. PATIENTS' DATA AFTER APPLYING DATA ENGINEERING

Patient ID	AGE	Gender	BMI	H. Blood Pressure	L. Blood Pressure	SPO2	Shortness of breath	Chest pain	: Pain or discomfort in the jaw, neck, or back	Palpitation	Cold sweat	Left-Hand Pain	Nausea or vomiting	Patient in Exercise or fatigue	Do you have a family history of chronic disease? (first- or second-degree relatives)	Do you currently suffer from a chronic disease?	Have you ever been that you had a "heart attack?	Are you a Smoker?
1	33	Female	47.4	12	8	99	no	no	yes	no	no	yes	no	rest	yes	no	no	no
52	69	Male	28.3	18	8	87	no	yes	no	no	no	no	yes	rest	no	no	yes	no
136	22	Male	22.3	11	8.5	98	no	no	no	no	no	no	no	rest	no	no	no	yes
191	51	Male	31.8	17.5	9.5	95	no	no	yes	no	no	no	no	exercise or fatigue	yes	no	no	no
212	65	Female	19.3	13	8	96	no	no	no	no	yes	no	yes	rest	yes	no	no	no

TABLE III. PATIENTS' DATA AFTER APPLYING MEDICAL GUIDELINES

Patient ID	**AGE**	**Gender**	**BMI**	**H. Blood Pressure**	**L. Blood Pressure**	**SPO2**	**Shortness of breath**	**Chest pain**	**: Pain or discomfort in the jaw, neck, or back**	**Palpitation**	**Cold sweat**	**Left-Hand Pain**	**Nausea or vomiting**	**Patient in Exercise or fatigue**	**Do you have a family history of chronic disease? (first- or second-degree relatives)**	**Do you currently suffer from a chronic disease?**	**Have you ever been that you had a "heart attack?**	**Are you a Smoker?**
1	**33**	**Female**	**47.4**	**12**	**8**	**99**	**no**	**no**	**yes**	**no**	**no**	**yes**	**no**	**rest**	**yes**	**no**	**no**	**no**
52	**69**	**Male**	**28.3**	**18**	**8**	**87**	**no**	**yes**	**no**	**no**	**no**	**no**	**yes**	**rest**	**no**	**no**	**yes**	**yes**
136	**22**	**Male**	**22.3**	**11**	**8.5**	**98**	**no**	**no**	**no**	**no**	**no**	**no**	**no**	**rest**	**no**	**no**	**no**	**no**
191	**51**	**Male**	**31.8**	**17.5**	**9.5**	**95**	**no**	**no**	**yes**	**no**	**no**	**no**	**no**	**exercise or fatigue**	**yes**	**no**	**no**	**no**
212	**65**	**Female**	**19.3**	**13**	**8**	**96**	**no**	**no**	**no**	**no**	**no**	**no**	**no**	**rest**	**yes**	**no**	**no**	**no**

C. Evaluation Medical Features

Evaluating medical features within a telemedicine framework is crucial for ensuring remote healthcare delivery's effectiveness and quality. This step is done by analysing previous studies, identifying the challenges they faced, and working on adding new features that contribute to facing these challenges. In alignment with the relevant research [15], We recycled data from several sensors, including SpO2 and blood pressure monitors, and merged it with textual inputs, including a comprehensive set of 14 indications. The signs included elevated and decreased blood pressure readings, oxygen saturation levels, rest periods, palpitations, dyspnea, thoracic pain, body temperature, cephalalgia, and discomfort in the left hand. Nevertheless, more new medical features were utilised to achieve the research objectives. The latest essential features derived from patients and considered are the patient's age, gender, BMI, and medical history. The importance of these factors is evident through their impact on the diagnosis process, as age is an essential factor in such cases [16] given that a person over 40 is more susceptible to one of the emergency cases covered by the application than other age groups. At the same time, a high body mass index is associated with some medical conditions, such as diabetes and heart attacks [45]. The patient's medical history also provides additional information, including whether the patient has been exposed to previous crises or has suffered from a chronic disease or whether a family member (first or second degree) has suffered from a chronic disease, in addition to more symptoms of medical conditions such as stroke and diabetes. Combining these factors enhances the accuracy of diagnosis, improves patient outcomes, and can lead to more personalised and effective emergency care [16].

D. Proposed the Mathematical Model

Rule-based systems represent the simplest form of artificial intelligence (AI) [46]. RBSs articulate knowledge as production rules, not as a declarative, static collection of tangible entities. Domains that allow knowledge expression through heuristics or guidelines are suitable for Rule-based models. They are ideal for diagnostic and classification tasks. Two advantages facilitate the creation of rule-based systems. i) The explicit delineation of the expert's reasoning allows for anticipating their approach to the problem; ii) the system does not require an extensive training dataset [47]. The rule comprises two components: the IF component and the THEN component. We refer to the IF segment as the antecedent or premise (or condition) and the THEN segment as the consequent or conclusion (or action). Therefore, we can formulate a fundamental principle: (IF antecedent, THEN consequent). The rule examines the logical expression in the premise, and if the expression is true, it states the integrity of a fact regarding an entity or a category of entities. A general rule may possess several antecedents connected by various logical operators, including AND, OR, or a combination [46]. All data for one user (Age, Gender, BMI, H/L Blood pressure, SPO2, medical history, and Symptoms of diseases) are the input variables to the initial diagnosis module. Our proposed framework, RIDF, has more than one rule. (A) is one type of a medical feature, (X) is the medical range, (B) is considered the score level, and (Y) represents the score value. The relation among (A, B, Y, and X) is given in the equations (1)– (4).

$$\text{IF}(\mathbf{A\ isX_1})\ \mathbf{AND}(\mathbf{A\ isX_2})\ \ldots\ldots\mathbf{AND}(\mathbf{A\ isX_n})\quad \text{THEN}\ ((\mathbf{B})\ \mathbf{is\ \ Cluster}\ (\mathbf{Y})\ ) \tag{1}$$

Where: $X = X_1 \cap X_2 \cap \ldots\ldots \cap X_n$

$$\text{IF}(\mathbf{A\ isX_1})\ \mathbf{OR}(\mathbf{A\ isX_2})\ \ldots\ldots\mathbf{OR}(\mathbf{A\ isX_n})\quad \text{THEN}\ (\mathbf{B\ is\ \ Cluster}\ (\mathbf{Y})\ ) \tag{2}$$

Where: $= X_1 \cap X_2 \cap \ldots\ \ldots \cap X_n$

$$\mathbf{Y = Y_1\ ANDY_2\ AND\ \ldots..ANDY_n} \tag{3}$$

Where: $Y = Y_1 \cap Y_2 \cap \ldots\ldots \cap Y_n$

$$\mathbf{Y = Y_1\ ORY_2\ OR\ \ldots..ORY_n} \tag{4}$$

Where: $Y = Y_1 \cup Y_2 \cup \ldots\ldots \cup Y_n$

The proposed RIDF framework includes two computational rule-based algorithms. The first algorithm is the RIDF triaging algorithm, which is developed based on the (IF-THEN) rules derived from the patient's information and medical guidelines presented in Table 4 to determine the emergency triage level for the patients. The RIDF triaging algorithm assigns the triage level depending on the patient's textual information and vital signs according to the medical protocols in Table 4. The RIDF triaging algorithm output is tagged with one of the five classes of triage: risk, urgent, sick, cold case, and normal. The following proposed algorithm in the RIDF framework is the RIDF diagnosis algorithm. The algorithm has been developed using the (IF-THEN) rules based on the patient's information and the medical guidelines provided in Table 4 to infer three main outputs: (1) to identify the chief complaint as an "initial diagnosis" based on a heart disease evaluation and (2) to generate suggestions systematically.

IV. RESULTS AND DISCUSSION

The proposed Remote Initial Diagnosis Framework (RIDF) was evaluated using a dataset of 250 patients, each with varying medical issues, including Hypertension, respiratory problems, heart attacks, and strokes. We tested the system in a simulated environment, which provided both triage and initial diagnosis based on sensor data and patient-reported information. The RIDF achieved an overall

triage accuracy of 99.1%, indicating that the system is highly effective at classifying patients based on their emergency level. Table IV shows the performance metrics (precision, recall, F1-score) across five categories: Normal, Cold Case, Sick, Urgent, and Risk. When juxtaposed with the alternative frameworks, [15][16]. RID exhibited the best performance. They achieved lower accuracy rates than RID, which has 98.5% accuracy. Moreover, we evaluated accuracy and recall by employing a macro-averaging approach, which examines each class's statistics independently before computing the average. In our multi-class environment, where the distribution of instances across categories may fluctuate, our strategy guarantees that each class is afforded equal importance.
The subsequent courses were associated with additional outcomes, including Precision, Recall, and the F1-score of RID: 97.9 %, 100 %, and 98.9 % for normal; 100 %, 100 %, and 100 % for cold cases; 98.6%, 100 %, and 99.3 % for sick; 97.3 %, 97.3 %, and 97.3 % for urgent; and 100 %, 100 %, and 100 % for risk cases. Figure 6 illustrates these findings. The RID algorithm proficiently classified all instances. The quantity of false positives (FP) and false negatives (FN) was minimal. The RIDF approach parallels how physicians and specialists convey guidance to their patients. As a result, the RIDF methodology exhibits greater accuracy compared to [15][16]. Table IV displays the outcomes derived from the categorisation performance measures. The results demonstrate that the RID algorithm achieved a superior ranking relative to others and enhanced performance compared to another algorithm [15][16]. This is due to its ability to reduce the overlapping of medical features. Its straightforward structure and rapid decision-making capabilities, grounded in rule-based principles, render it pertinent for real-time emergency triage applications.
Moreover, experienced professionals in emergency medicine have conducted extensive examinations of patient records to ensure the accuracy of all medical information. Close monitoring lends itself to better quality care. It makes patients more confident in health technologies and committed to accuracy, and they are safe. In a nutshell, this sort of collaboration helps provide more effective healthcare services that are guaranteed to improve patient results.

TABLE IV. PERFORMANCE EVALUATION OVERALL PROPOSED FRAMEWORK

Tirage	Precision	Recall	F1-score
Normal	**97.9**	**100**	**98.9**
Cold case	**100**	**100**	**100**
Sick	**98.6**	**100**	**99.3**
Urgent	**97.3**	**97.3**	**97.3**
Risk	**100**	**100**	**100**
Overall Accuracy 98.4			

We simulated the application's interface and technical implementation in our lab with the following setup:

- Backend: Python 3.10.1, Flask framework
- Frontend: HTML, CSS, JavaScript
- Database: Cloud-based SQL
- Operating System: Windows 11 Pro
- Hardware: 16GB RAM, Core i7 10th Gen CPU

This lightweight and scalable framework, "TeleMedQuick", ensures smooth performance and provides an efficient and user-friendly interface for real-time telemedicine applications.

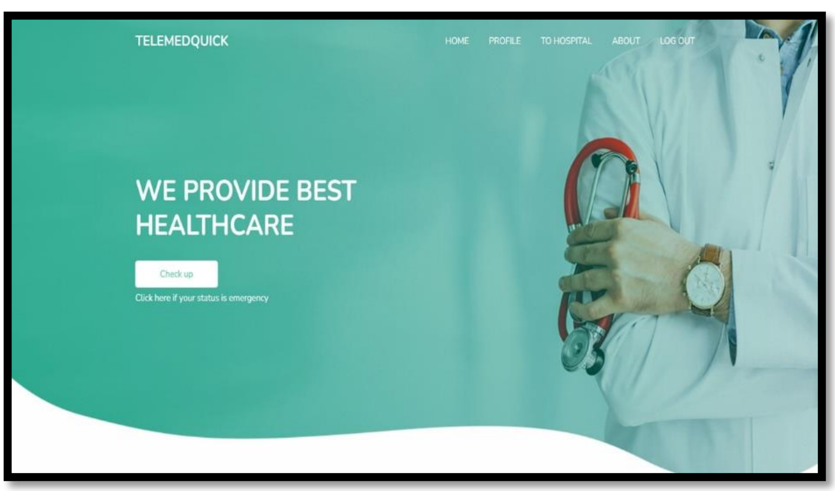

Figure 4: "TeleMedQuick" application

The patient enters his data to create his profile, including the following information (Name, Age, Gender, Height, Weight, Smoker or not, medical history). Then, he moves to conduct the heart disease test, as shown in Figures 5 and 6.

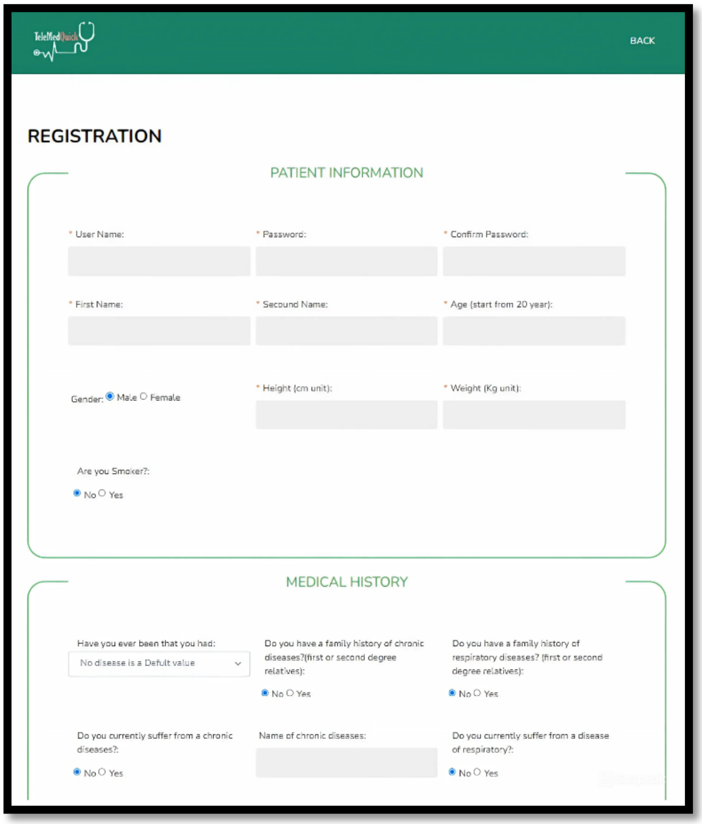

Figure 5: Patient profile information

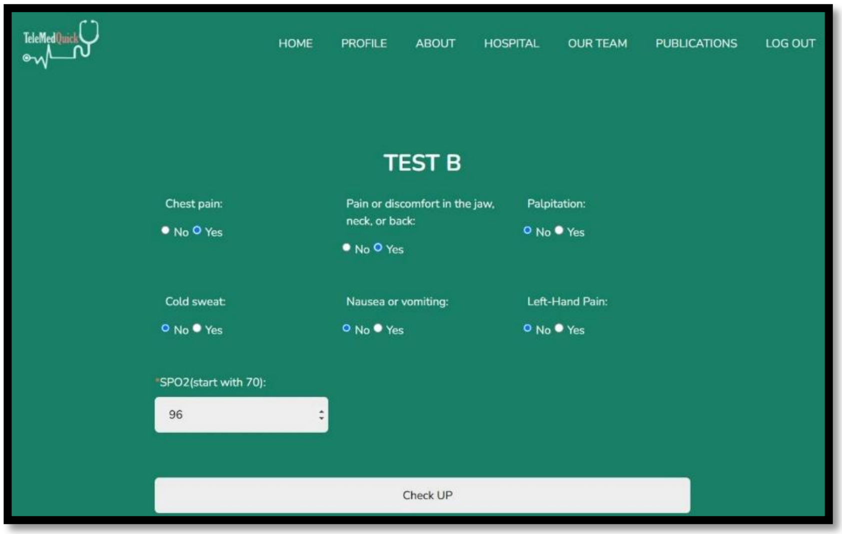

Figure 6: Heart disease test

Table V compares our proposed Remote Initial Diagnosis Framework (RIDF) and existing frameworks. The RIDF framework has overwhelming advantages compared with previous solutions for overcoming the different challenges in telemedicine. Our approach is particularly suitable for using a greater variety of medical information, including non-sensory textual and sensory sensor inputs. As a result, it improves the accuracy of diagnosis. Thus, our RIDF simultaneously performs triage and initial diagnosis. Hence, both steps are well coordinated to avoid delays in care. This dual capability allows for better utilisation of resources by reducing unnecessary hospital visits, thus allowing quiet identification of critical cases for early intervention. Further, the proposed system is scalable, hence able to care for more patients without compromising accuracy and speed. Consequently, our system outperforms existing methods in terms of accuracy but also provides a scalable and integrated solution for remote healthcare, especially for settings with few resources or high demand, hence, a giant stride in Telemedicine.

TABLE V. TABLE 7: OUTCOMES

Patient ID	Triage Level	Chief complaints	Advice
1	Sick	Heart attack	Your symptoms may indicate a heart attack; please see a doctor as soon as possible to ensure your health condition
52	Urgent	Heart attack, High Blood Pressure	Your symptoms may indicate a heart attack; please go to the hospital as soon as possible to receive the necessary treatment.
136	Normal	No diseases	
191	Sick	Heart attack	Your symptoms may indicate a heart attack; please see a doctor as soon as possible to ensure your health condition
212	Cold Case	No diseases	Always keep an eye on your health status, as you may be at risk of a heart attack) in the future because of your medical history and age over 40.

V. CONCLUSION

This study proposed a novel Remote Initial Diagnosis Framework (RIDF) for improving telemedicine services for chronic heart disease patients. Integrating the Internet of Medical Things (IoMT) and artificial intelligence (AI) technologies has empowered the framework to conduct real-time triage and initial diagnostics with an average accuracy of 98.4%. The results show that the framework has successfully overcome several significant limitations of existing systems in incorporating multisource data and providing real-time decision-making capabilities. Such dual functionality in simultaneously triaging and diagnosis is designed to decrease emergency care delays and improve resource allocation within a healthcare setting. Also, the rule-based algorithms guarantee the accuracy and reliability of the system, for example, by referring to the high-performance indicators concerning all levels of emergencies. Integrating sensory and non-sensory information enhances the thoroughness and accuracy of remote assessments.

Meanwhile, capabilities for real-time processing allow quick and informed decision-making at critical medical events. Its lightweight and highly scalable architecture makes it wonderfully suited for deployment in healthcare settings with constrained resources. In this respect, future research should focus on better incorporation of the most recent artificial intelligence approaches, especially deep learning architectures, to further improve diagnostic accuracy and adaptability. The hypothesised framework would then be tested in the setting of other chronic diseases, including diabetes and respiratory disease, to assess its effectiveness within more extensive real-life clinical settings to assure scalability and sustainability. Exploring these pathways can potentially strengthen Telemedicine, enabling better patient outcomes and building a more effective healthcare delivery system.

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