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Sensor Data Fusion in Healthcare Monitoring System with Appropriate Rule-based Model for Error Reduction

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Abstract: Healthcare monitoring System (HMS) is involved in the continuous and periodic evaluation of the patient or individuals. The HMS uses multiple sensors to monitor the health status of patients. However, the conventional methods are subjected to errors in the computation of data in the environment. Hence, this paper proposed an Optimized Rule-based Sugeno Fuzzy Hidden Markov Model Stacked Deep Learning (ORSF-HMM-SDL) for error reduction in the environment. The proposed ORSF-HMM-SDL model uses the Associative rule-based for the computation of the health status of patients. The proposed model utilizes the optimized fuzzy system for the estimation of the features with the classification using stacked deep learning. The ORSF-HMM-SDL uses the Sugeno Fuzzy interface model to assess the health status of patients. The proposed ORSF-HMM-SDL estimates the Hidden Markov Model (HMM) for the computation of features for the error computation. With the estimated features the ORSF-HMM-SDL model computes deep learning for the classification with the stacked model. data fused with the sensor are applied and classified with the deep learning model. The simulation results demonstrated the effectiveness of different fusion techniques—ORSF-HMM-SDL Fusion, Kalman Filter Fusion, Deep Learning (DL) Based Fusion, and SVM Based Fusion—in healthcare monitoring systems. The study evaluates their performance using metrics such as accuracy, sensitivity, specificity, precision, recall, F1-score, error rate, latency, and throughput. The Deep Learning Fusion method achieves the highest accuracy of 96.5% for heart disease detection, 94.2% for diabetes, and 95.8% for hypertension, with an overall accuracy of 98.3% for healthy individuals. The method also records a high F1-score of 98.3% for healthy individuals, 94.2% for heart disease, and 91.7% for hypertension. In comparison, ORSF-HMM-SDL Fusion shows strong performance with an overall accuracy of 94.8%, sensitivity of 92.3%, and specificity of 96.1%, along with a low error rate of 5.2%. The Kalman Filter Fusion and SVM Based Fusion methods, while effective, show slightly lower performance across most metrics, with Kalman Filter achieving 93.0% accuracy and Deep Learning showing superior performance with 700 data points/min throughput. These findings demonstrate that while deep learning offers the highest overall performance.

Index Terms: Healthcare Monitoring, Sugeno Fuzzy, Hidden Markov Model (HMM), Associative Rule, Fusion Data.

1. Introduction

A Healthcare Monitoring System (HMS) is an approach aimed at the identification, recording, and monitoring of patient health parameters on an SS, Real, or periodic basis. It uses wearables, sensors, and other IoT smart devices to capture vital data as the heart rate, blood pressure, blood oxygen levels, and glucose levels [1,2]. This data is then sent out to a central site, which can be cloud-based, for processing by sophisticated computer code that employs various forms of artificial intelligence and machine learning to look for signs of disease and other health problems [3]. Telemonitoring

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is also among HMS features, which allows evaluating patients state without outpatient visits [4]. Furthermore, the system may contain a sounding technique that enables it to raise alarm in case of an emergency to the care givers or the medical personnel [5]. HMS enables better care delivery since it reduces the time and expenses linked to identifying diseases in the early stages or readmitting patients to the hospital since patient distinctive data is used to customize treatment approaches. With the management of EHRs to HMS, secure access to their past records helps HMS to provide valuable data to the physicians for management purposes [6,7]. HMS platforms under complexity may include telemedicine, whereby the patient/healthcare provider transmits/receives data and information using communication technology. HMS have central role in the coordinated treatment of chronic diseases such as diabetic, hypertensive, cardiovascular diseases by observing and intervening at the right time [8]. HMS can be interfaced with other mobile applications for the provision of information on current trends in health, prescription, and health goals of a particular user [9]. In the public health interest, HMS may centralize de-identified data to investigate the occurrence of specific disease conditions at considerable scale for epidemiological analysis and modelling, with a view to readiness to address future epidemic or designated resource distribution [10]. However, issues of data confidentiality, compatibility, and cost issues are some of the barriers that have to be resolved for it to be optimized and made affordable for use by all. The health care monitoring systems are revolutionizing the provision of services and instituting patient centrism in health care provision [11]. Sensor data fusion occupies a central position in the Healthcare Monitoring System in a bid to produce accurate, reliable and holistic health monitoring. Sensor data fusion consists of combining data collected from one or many sensors including heart monitor, blood pressure meter, blood glucose meter, and motion sensors. Since various data sources are integrated, noise is minimized, increasing accuracy, and all patient information is presented in one place [12]. Further, the advanced fused data through time contains the application of Kalman filters, Bayesian networks, and deep learning models for real-time data analysis.

This combination allows for the recognition of refined patterns which include association of physical activity with changes in blood glucose level, stress recognition with the use of heart rate variability and galvanic skin response among others [13,14]. For instance, smartwatches or other smart accessories that are embedded with plural sensors can effectively monitor a patient's consummate vital signs as well as measuring the surrounding environmental conditions while the fused data corresponding to these aspects can be wirelessly transferred to a base station for anomaly identification [15]. In emergency situations, the system is capable of emitting alerts depending on the values acquired from the integrated sensor thus informing timely action by the medical team [16]. Furthermore, integrated sensor data enhances the provision of analytic predictions, which can help lower the risk of a person's health [17,18]. It also promotes better fees when considering the results of such rearing of patients as well as refined usage of resources in systems of medical care. Still, some challenges for example, synchronizing the data streams, calibrating the sensors, and protection of data may be vital for the proper application of the sensor data fusion in healthcare monitoring [19]. Healthcare monitoring with sensor data fusion defines a technological advancement in the delivery of patient care, in that is informed by aggregated data from a variety of sensors. This approach involves acquiring data from various gadgets such as heart monitor; blood pressure sensors; accelerometer; and glucose meter and then integrate the data into one dataset that has low noise and high credibility [20]. Using Kalman filter, fuzzy logic or machine learning algorithms, sensor data fusion incorporates all the above-turn mentioned data streams in real time. Based on the entire set of gathered data, the system finds combined and intricate health patterns, like, associating the dynamics of physical activity with the patterns of glucose level, or distinguishing signs of emerging cardiovascular problems using combined data on Heart Rate Variability and blood pressure [21,22].

In case of a healthcare monitoring system, data fusion in sensors is an effective means to perform anomaly detection and predictive analysis that will assist the healthcare givers to prevent possible future challenges [23]. For instance, with the wearable devices, a patient's physiologic data are collected and fused to alert during diseases event like arrhythmia or low oxygen levels. Such monitoring sharpens emergency response and allows controlling patient's condition without constant revisits to the hospital [24]. Healthcare Monitoring System with sensor data fusion with error reduction in the health monitoring system leads to improved health monitoring accuracy [25]. Multisensor fusion integrates data from various sensors including, heart rate monitors, temperature sensors and accelerometers to give a complete picture of a patient's status [26]. Reducing errors due to noisy sensors, environmental noise and discrepancies in data is done through Kalman filtering, wavelet transforms and machine learning noise reduction technology [27]. This integration also makes sure that important measurements including vital signs are acquired accurately even in complex environment. For instance, several sensor read-outs that contain motion artefact in signals derived from a single sensor can effectively be cross-checked to eliminate the artefact [28]. In the implementation of real-time surveillance, but also significantly boosts the effectiveness of risk forecasting and preventive measures by the side of the healthcare industry [29,30]. Also, improvement in error correction for sensor data fusion leads to improved identification of anomalous patterns and decision making regarding important episodes in critical pathologies such as arrhythmias or hypoglycemia, with fewer false positive and negative results. It also improves the dependability of RPM solutions that are vital for the treatment of chronic illnesses or for tracking post-operations patients. This is because, by guaranteeing the effective data integrity, this approach builds confidence in the deployment of the technologies in the healthcare sector hence proving the path to improved more patient centered healthcare.

This paper is in presenting a comparative study of different fusion methodologies used in healthcare monitoring and focusing especially on the ORSF-HMM-SDL Fusion, Kalman Filter Fusion, Deep Learning (DL) Based Fusion and SVM Based Fusion. The paper computes these techniques based on important parameters including accuracy, sensitivity,

specificity, precision, recall, F1-score, error rate, latency, and throughput, and hence allows a comparative assessment of the various techniques. In this work, Deep Learning methods are established to be highly accurate and with a higher F1-score than other methods they are compared to as well as identifying the ORSF-HMM-SDL Fusion as another viable method for health condition classification due to its robustness. Finally, we discuss the practical concerns like latency and throughput not previously mentioned in most papers which are important in real-time applications such as healthcare. Its findings show that particular guidance on selecting the right fusion techniques depending on the need of the fused system can be gotten from this work making it a reference point for future work on healthcare sensor fusion systems. According to the performance analysis, DL-Based Fusion is always the highest for all the experiments conducted as it has the 96.5% highest accurate on heart disease detection. It also shows the highest values of Sensitivity: 95.0%, Specificity: 97.0%, Precision 94.5% and Recall or True positive rate of 96.0%. In addition, Deep Learning yielded the least error rate of 3.5% and described the greatest throughput of 700 data points/minute and least latency of 0.35 Seconds. In its turn, ORSF-HMM-SDL Fusion has similar figures with 94.8% of accuracy, 92.3% of sensitivity, and 96.1% of specificity, so this creates balance between performance and effective computation time. The fusion techniques which perform a little low are the Kalman Filter Fusion and SVM based Fusion with an accuracy of 93.0 % and 91.5 % respectively, but it has higher error rate and latency than other fusion techniques.

2. Related Works

Over the years there has been vast improvements in Healthcare Monitoring Systems (HMS), where and successful integration and analysis of physiological parameters gathered by sensors coupled with efficient computational processing enhances the quality of treatment. There has been a track of studies concerning the combination of wearable devices, IoT sensors, and real time data in order to develop effective monitoring systems. Researchers have analyzed methods of working with sensor data by using different methods such as Kalman filter, Bayesian inference, and machine learning algorithms to improve the reliability of the data. Furthermore, recent focus has been made to solve issues like noise elimination, the problem associated with synchronizing multiple streams of sensor data, and even the problem of how to securely transmit health information. Some ideas have also been pointed out in several works showing that HMS plays a critical role in managing chronic conditions, remote patient monitoring, and emergency response. These studies also reveal that the fused data from sensors can effectively be utilized for the task of anomaly detection, for risk assessment for health and for developing individualized treatment plans. Other related studies have also explored the effects of error reduction strategies employed in the integration of sensor data and large improvements in both accuracy and precision were observed. However, issues connected with data exchange, computational efficiency of algorithms, and general scalability to a broad variety of applications still present some of the most interesting research topics.

In the same year, Lian et al. [6] proposed a health assessment method-attribute importance modeling with BRB showing enhanced reliability in system safety assessment. More recently, in Bhukya and Manchala (2022) [7] with the use of metaheuristic rough set-based feature, selection using rule-based classification for the medical data analysis using Apache MapReduce, performance and scalability were demonstrated. Wireless sensor networks were the subject of analysis for Sun et al. (2022) [8], where they present a fault diagnosis model that is based on the BRB approach and the use of a power set; sensor data reliability and the ability to consider a wide range of possible outcomes were highlighted. Shirali et al. (2024) [9] proposed an error-correcting IoT event log technique to increase corrective interactions for more accurate data. Using the fuzzy logic system in the context of the healthcare specific application, Nagarajan and Thirunavukarasu, (2022) [10] have formulated a neuro-fuzzy framework for disease prediction using fuzzy integration with machine learning. Anikwe et al. (2022) [11] have discussed mobile and wearable sensors in health monitoring including state-of-art, trends and future by categorizing into data driven system. More specifically, Lv et al., [12] conducted large-scale healthcare data fusion, where multi-sensors were utilized and thus showed an example of hyperscale fusion applying to complicated environment. The proposed model by Xu et al. (2022) [13] was applied to fault diagnosis of machines during maintenance and primarily considered the weighted soft-voting rule and the multi-attentional network to support multi-scale information integration. Rambabu et al. [14] also proposed an IoT-based rule management model for integrated environment in another year 2024 for varied system requirement. Last but not the least, Kierner et al. (2023) [15] presented the type of hybrid architecture inclusive of rule-based reasoning and machine learning in clinical decisions and underlined the complementarity of both approaches to improve the health-care results. In combination, these investigations make a significant contribution to the development of healthcare monitoring systems by pointing out limitations in the provided data fusion, predictive modeling, and integrated systems.

Cavaliere et al. (2024) [16] have put forward a HF-RBFN model for crop health assessment that may also be extended for other predictive models in healthcare systems. Sarker et al. (2024) [17] offered a taxonomy of multi-aspect rule-based AI models for transparent and intelligent cybersecurity stressing its applicability to automation of CI such as healthcare sector. Elidolu et al. (2023) [18] used rule-based Bayesian network for assessing the operational risk, and provides the implication of using evidential reasoning for medical diagnosis. In maintenance optimization, Sun et al. (2024) [19] proposed a new rule-based method with dynamic parameter range; this can be adapted to healthcare monitoring for the purpose of predictive maintenance of the medical equipment. In Pramila et al. (2023) [20] proposed medical aiding robots which are in line with the data fusion, as observed in improvements to robotic health care. Likewise, Shaik et al. (2023) [21] offered an extensive and focused survey of (AI-driven) remote patient monitoring and its challenges, as well as state-

of-the-art advancements. Machine learning approach has been utilized in combination with rule-based system which has been described in Jha et al., 2022 [22] whereby a neural-fuzzy hybrid rule-based system was used for efficient heart attack prediction. Gawde et al. (2024) [23] rightly articulated explainable predictive maintenance using multi-sensor data fusion and illustrated that it is equally applicable in healthcare context. More recently, Geng et al. (2024) [24] investigated evidential rule fusion for wearable human activity recognition that serves as a wider justification of the technology in personalized healthcare. Kumar et al. (2023) [25] has provided an overview of applications in sensor-based IoT systems and Jiang et al. (2024) [26] provided a machinery fault diagnosis system that can be possibly adapted to healthcare devices using a semi-supervised framework.

Zafeiropoulos et al. (2024) [27] assessed the ontology-based monitoring for Parkinson's disease with graph neural networks as an example of knowledge graphs applied to health monitoring. Fadhel et al. (2024) [28] therefore undertook a systematic review of information fusion techniques particularly for use in smart urban contexts where health care related information would be integrated into smart cities. In Christopher et al. (2023) [29] , A QoS-aware fusion model based on Earthworm and Deer Hunt Optimization was proposed for efficient routing in wireless sensor networks of healthcare IoT for better understanding of the data transmission efficiency. Motwani et al. (2022) [30] presented smart healthcare frameworks using machine learning focusing on their capability of monitoring and diagnosing in real-time. Gaw et al. (2022) [31] investigated different approaches of merging the multi-modal data in an effort to advance the system performance; an aspect that has potential to improve the decision making required in healthcare monitoring. Meng et al. (2023) [32] described the application of case-based reasoning and rule-based reasoning fusion for constructing bridge models for the improvement of the presented example of using such methodologies in modeling of complex healthcare systems. In their scoping review, Gawde et al. (2023) [33] investigated multi-fault diagnosis employing sensor fusion and proposed intending to enhance the dependability of Healthcare Monitoring Systems. Most of the approaches rely on significant rule-based systems and while these methods are comprehensible, they are not very good at dealing with highly dynamic or unknown situations since the rules are set and on a rather more solid baseline. For instance, neural-fuzzy hybrid systems or hierarchical fuzzy rule-based frameworks depends on the extent and calibre of the initial rule base and thereby the system's potential vary between real world conditions.

Furthermore, with the increasing implementation of multi-sensor data fusion in the health care systems, certain problems are associated; including a high level of computational requirements, data heterogeneity, and data synchronization. Despite the credentials that come with evidential reasoning or even the Bayesian network several of them are scalability problems whenever used for large datasets or in real-time. Also, in most models, the reliance on higher quality labeled datasets is considered; however, acquiring such data can be expensive and time-consuming in healthcare contexts with potential restricted generalizability. Another common limitation is that these models often do not pay enough attention to how these systems perform under adverse condition, such as failure of sensors, disruptions in communication or cyber-attacks. A substantial number of the available publications concern themselves with cybersecurity yet lack a structured but general way of incorporating fault tolerance or security mechanisms into their methodologies. Besides, the interpretability and transparency of the artificial intelligence are still a problem while more complicated fusion or reasoning strategies are possible to be a barrier to selecting them for the most important healthcare applications, especially if explainability is critical. Finally, although there is much research documenting potential benefits, few interventions have received substantial empirical support in the real world or adequately address relevant concerns as the ethical considerations about patient confidentiality and data security in IoT-Based Health Monitoring Systems. Overcoming these limitations remains critical to supporting these innovations' feasibility and ethical utility for implementation in health systems.

3. Proposed Rule based Sugeno Fuzzy -HMM (RSF-HMM-SDL)

Based on fuzzy logic and Hidden Markov Models (HMMs) and rule-based reasoning, for sensor data fusion in healthcare monitoring systems, the proposed Rule-based Sugeno Fuzzy Hidden Markov Model (RSF-HMM-SDL) integrates fuzzy logic, HMM, and rule-based reasoning for increasing the accuracy, flexibility, and reliability of the healthcare surveillance. In this framework, the Sugeno fuzzy inference system is used for the processing of imprecise and uncertain sensor data and to filter and integrate various sources of data such as heart rate, blood pressure and temperature to give meaningful health status information. The third part of the proposed system is a fuzzy logic component that enables the system to manage uncertainties associated with the readings from the sensors, which should help the system to withstand sensor noise or missing data. Time dependencies in the health status of patients are modelled with the integration of the Hidden Markov Model (HMM) to model sequential data typical of the medical field such as periodic monitoring of vital statistics. It allows the ORSF-HMM-SDLto extrapolate the future states of health and facilitate better decision-making in relation to real-time observation. The additional component of the ORSF-HMM-SDLto the previous sections of the textual input is the rule-based system added to the model to enable the healthcare professionals to follow up to the reasoning component behind the system tracing their prediction based on medical knowledge and predefined rules. the proposed Rule-based Sugeno Fuzzy Hidden Markov Model (RSF-HMM-SDL) for sensor data fusion in healthcare monitoring systems with derivations and equations, we will break down the model into its key components: The three systems used in this paper include the Sugeno fuzzy inference system, the Hidden Markov Model (HMM), and the rule-based reasoning system. The other aspect of uncertainty in the system is addressed by employing the Sugeno

fuzzy inference system. Sugeno fuzzy inference system possesses the following format; it contains fuzzy rules and a fuzzy inference system. The Sugeno inference mechanism computes the output as a weighted average of the outputs of all the rules. In the Sugeno FIS, the output y is obtained by aggregating the results of all rules. The result of each rule is weighted by the degree of membership of the input in the fuzzy sets. The output y is calculated using equation (1)

$$y = \frac{\sum_{i=1}^{N} w_i f_i(x_1,x_2)}{\sum_{i=1}^{N} w_i} \tag{1}$$

In equation (1) w_i is the weight associated with the i-th rule, $f_i(x_1, x_2)$ denoted as the output of the i-th rule. The weight w_i is computed based on the degree of membership of the input in the fuzzy sets stated in equation (2)

$$w_i = degree\ of\ truth\ of\ rule\ i \tag{2}$$

The Hidden Markov Model (HMM) is used to model the evolution of the patient's health state over time, where the health states are hidden (i.e., not directly observable). Let S_t represent the state of the system at time t. Let O_t represent the observable data with Transition Probability for transitioning from state S_{t-1} to state S_t at time t is stated in equation (3)

$$P(S_t \mid S_{t-1}) for\ t = 1,2, \dots, T \tag{3}$$

Emission Probability for observing O_t given state S_t is defined in equation (4)

$$P(O_t \mid S_t) for\ t = 1,2, \dots, T \tag{4}$$

The initial probability distribution over states is $P(S_1)$. The forward algorithm is used to calculate the probability of the observed sequence of data given the model parameters. Let αt(i)\alpha_t(i)αt(i) represent the probability of observing the sequence $O_1, O_2, \dots, O_t$ and being in state $S_{t=1}$ at time t. The recursive calculation of $\alpha_t(i)$ stated in equation (5)

$$\alpha_t(i) = P(O_1, O_2, \dots, O_t, S_t = i) \tag{5}$$

This can be computed using the following recursion defined in equation (6)

$$\alpha_t(i) = \sum_{j=1}^{N} \alpha_{t-1}(j)\, P(S_t = i|S_{t-1} = j) P(O_t|S_t = i) \tag{6}$$

In equation (6) N is the number of states, $P(S_t = i|S_{t-1} = j)$ stated as the state transition probability, $P(O_t|S_t = i)$ represented as the emission probability. The ORSF-HMM-SDL incorporates a rule-based system to adjust the transition and emission probabilities of the HMM. These rules reflect domain-specific knowledge that may modify the model's behavior. A rule can modify the transition probabilities $P(S_t \mid S_{t-1})$. If a patient's heart rate exceeds a threshold, the transition probability to a more severe health state may increase. The modified transition probability could be expressed as in equation (7)

$$P(S_t = i|S_{t-1} = j) = P(S_t = i|S_{t-1} = j) + \Delta P \tag{7}$$

In equation (7) ΔP is the adjustment based on the rule. Similarly, the emission probabilities $P(O_t \mid S_t)$ can be modified by rules based on sensor readings. If the sensor data indicates high blood pressure, the emission probability for the "ill" state could be increased as in equation (8)

$$P(O_t \mid S_t = i) = P(O_t \mid S_t = i) + \Delta O \tag{8}$$

In equation (8) ΔO represents the adjustment based on the rule. In the ORSF-HMM-SDLmodel, the fuzzy output from the Sugeno FIS is used as the input to the HMM. The fuzzy logic system helps handle the uncertainty in sensor data, while the HMM tracks the state transitions over time. The final health state S_t at time t is determined by both the fuzzy inference system (for reasoning based on sensor data) and the HMM (for temporal reasoning based on state transitions). The overall model can be described as in equation (9)

$$P(s_t|O_1, O_2, \dots., O_t) = \frac{P(O_t|S_t)P(O_t|S_{t-1})P(s_{t-1}|O_1, O_2, \dots., O_{t-1})}{P(O_t|O_1, O_2, \dots., O_t)} \tag{9}$$

In equation (9) $P(O_t \mid S_t)$ stated as the emission probability, $P(O_t \mid S_{t-1})$ represented the transition probability, $P(s_{t-1}|O_1, O_2, \dots., O_{t-1})$ defined the probability of the previous state given all prior observations. The ORSF-HMM-SDL

combines the strengths of fuzzy logic and Hidden Markov Models. The Sugeno FIS helps handle the imprecision and uncertainty in the sensor data, and the HMM captures the temporal evolution of health states. By incorporating rule-based reasoning, the system can integrate expert knowledge to improve predictions and decision-making, especially in complex healthcare monitoring scenarios. The equations above demonstrate how these components work together to provide robust, real-time health state predictions based on sensor data.

3.1. Steps in Proposed ORSF-HMM-SDL for the Sensor Data Fusion

The proposed ORSF-HMM-SDL model for the sensor data fusion with the Healthcare monitoring shown in Fig.1 is stated as follows:

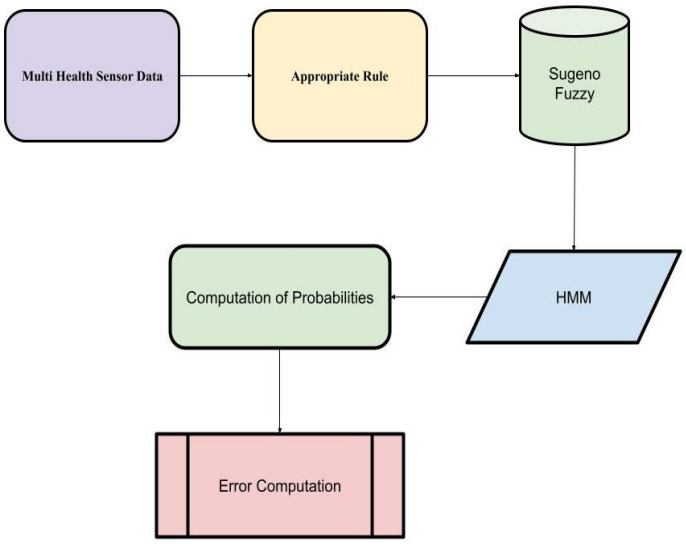


Fig.1. Flow chart of ORSF-HMM-SDL

A. Sensor Data Collection and Preprocessing

The first step is to gather data from various forms of sensors in healthcare for instance heart rate, blood pressure and pulse oximetry meters. Most of these sensors generate a large amount of data that is noisy and nonstationary and therefore requires preprocessing. Smoothing is then applied to eliminate the noise and ensure that the data sets are standardized and within a range of 0 & 1. The transformed data is acquired from the healthcare sensors, including heart rate, blood pressure and oxygen saturation level. Much of what is acquired by a sensor is inherently noisy and can include features that are not necessarily of interest. There is no difference between noise removal and normalization when their procedures can be formulated using equation (10)

$$x_{normalized} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{10}$$

In equation (10) x is the raw sensor value, $\min(x)$ and $\max(x)$ are the minimum and maximum values of the sensor data.

B. Fuzzy Rule-Based Data Aggregation

In this step, fuzzy logic is applied to handle uncertainty and imprecision in the sensor data. Each sensor reading is mapped to fuzzy sets such as "Normal," "High," or "Critical" using membership functions. For example, the membership degree of a reading x to a fuzzy set A is calculated using a piecewise linear function. The fuzzy rules are then defined to aggregate the data, such as

"If heart rate is High and blood pressure is Hypertensive, then health risk is Critical."

Fuzzy -rule produces a consolidated health risk level from multiple sensor inputs. This ensures that the sensor values are scaled to a range of [0, 1] for uniformity. To manage uncertainty in sensor data, fuzzy sets are defined for each sensor reading, and fuzzy rules are created to infer the overall health risk. For a sensor value x, the fuzzy membership degree for a fuzzy set A (Normal, High) is stated in equation (11)

$$\mu_A(x) = \begin{cases} \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \\ 0, & Otherwise \end{cases} \quad (11)$$

In equation (11) a, b, c define the fuzzy set's range.

C. Hidden Markov Model Construction

Once the fuzzy outputs are obtained, a Hidden Markov Model (HMM) is constructed to model the temporal evolution of the patient's health state. The HMM consists of hidden states (e.g., Healthy, Unstable, Critical), observations (sensor data or fuzzy outputs), initial state probabilities, transition probabilities, and emission probabilities. Transition probabilities, $P(S_t \mid S_{t-1})$, define the likelihood of moving between health states over time, while emission probabilities, $P(O_t \mid S_t)$, represent the likelihood of observing specific sensor values given a health state. These parameters allow the HMM to model temporal dependencies and probabilistic relationships in the data. The HMM models temporal changes in the patient's health state using:

- States (S): Hidden health states such as Healthy, Unstable, Critical.
- Observations (O): Sensor readings or fuzzy output values.
- Initial Probabilities ($P(S1)$): Probability of starting in a specific state.
- Transition Probabilities: Probability of transitioning between states stated as $P(S_t \mid S_{t-1}) = Probability\ of\ moving\ from\ state\ S_{t-1}\ to\ S_t$.
- Emission Probabilities: Probability of observing a value O_t given the state S_t: $P(O_t \mid S_t) = Probability\ of\ observing\ O_t\ in\ state\ S_t$.

D. Integration of Fuzzy Outputs into HMM

The fuzzy outputs are integrated into the HMM to dynamically adjust its parameters. Transition probabilities $P(S_t \mid S_{t-1})$ are updated based on the fuzzy risk levels, making the model more responsive to changes in health conditions. Similarly, emission probabilities $P(O_t \mid S_t)$ are refined using the fuzzy membership degrees, enhancing the accuracy of the observed data representation. For instance, if the fuzzy logic indicates a high risk, the HMM may increase the likelihood of transitioning to a Critical state. The fuzzy output modifies HMM parameters dynamically to better represent sensor data relationships. Dynamic Transition Adjustment computed with the Transition probabilities are updated based on fuzzy outputs defined in equation (12)

$$P(S_t|S_{t-1}) = P(S_t|S_{t-1}) + \Delta P \quad (12)$$

In equation (12) ΔP depends on the fuzzy risk level. Emission probabilities are refined as in equation (13)

$$P(O_t \mid S_t) = P(O_t \mid S_t) + \Delta O \quad (13)$$

In equation (13) ΔO is based on fuzzy membership degrees.

E. Probabilistic Inference and State Estimation

Using the constructed HMM, probabilistic inference is performed to estimate the most likely health state at any given time. This involves the Forward Algorithm, which calculates the probability of observing a sequence of data and determines the likelihood of being in each state. To predict the patient's health state over time, the Forward Algorithm calculates the probability of the observed sequence and estimates the most likely current state S_t.

F. Health State Prediction and Decision Making

Based on the estimated health state, the system predicts the patient's condition and triggers appropriate actions. For instance, if the state is identified as Critical, the system sends alerts to healthcare providers or caregivers. For stable states, the data are logged for continuous monitoring. This step ensures timely intervention and efficient resource allocation. Based on the most probable state (S_t):

- **Critical State**: Alerts are triggered.
- **Stable State**: Data is logged for monitoring.

The system continuously updates as new sensor data arrives.

G. Continuous Feedback and System Update

To adapt to changing conditions, the system incorporates continuous feedback. Fuzzy rules are updated periodically based on new data trends, and HMM parameters are retrained as needed. This dynamic update mechanism ensures that the ORSF-HMM-SDL remains accurate and reliable over time, accommodating variations in sensor data and patient conditions.

Associative Rule for the Sensor Fusion

With estimation of patterns and relationships between data from the sensors forms an integral component of the associative rules in the sensor fusion process in chosen applications. These rules aid in mapping of sensor data in order to find the overall health status of a patient when it comes to health monitoring. The process it involves is mining frequent patterns and accumulation of rules on how certain combinations of the sensor readings are associated with certain ailment. The associative rule might state:

"If this is high the chances are that the heart rate is high and the blood pressure is also high then health status is at risk."

These rules are developed through means of algorithms such as Apriori or FP-Growth, measures the correlation between the sensor values. Each rule can be written as $A \rightarrow BA$ where A (antecedent) is the set of vectors of conditions (high heart rate, high blood pressure, etc.) while B (consequent) is the result: health at risk. The strength of these rules is evaluated using metrics like Support, Confidence, and Lift:

Support Measures the frequency of the rule occurring in the dataset stated in equation (14)

$$Support(A \rightarrow B) = \frac{\boldsymbol{Frequency\ of\ (A \cap B)}}{Total\ Observations} \tag{14}$$

This indicates how often the conditions A and B appear together in the sensor data. Confidence indicates the likelihood that B occurs when A is observed. It is stated in equation (15):

$$Confidence(A \rightarrow B) = \frac{\boldsymbol{Frequency\ of\ (A \cap B)}}{Frequency\ of\ A} \tag{15}$$

The Higher confidence values suggest stronger predictive power of the rule. Lift computes how much more likely B is to occur given A compared to when B occurs independently. It is given in equation (16)

$$Lift(A \rightarrow B) = \frac{\boldsymbol{Confidence(A \rightarrow B)}}{Support\ (B)} \tag{16}$$

A lift value greater than 1 indicates a positive association between A and B. In sensor fusion, these rules help integrate heterogeneous data sources to provide a unified view of the patient's health shown in Fig.2. and Healthcare monitoring system model shown in Fig.3. For instance, multiple sensor readings (heart rate, oxygen levels, and temperature) are fused based on associative rules to classify the patient's health state into categories like "Normal," "Warning," or "Critical." Table 1 presents the Healthcare monitoring system for the based on rules.

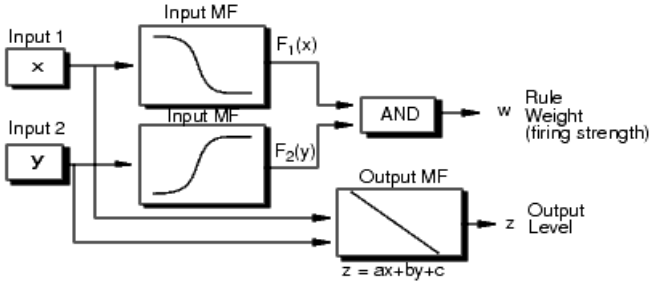


Fig.2. Sugeno fuzzy model

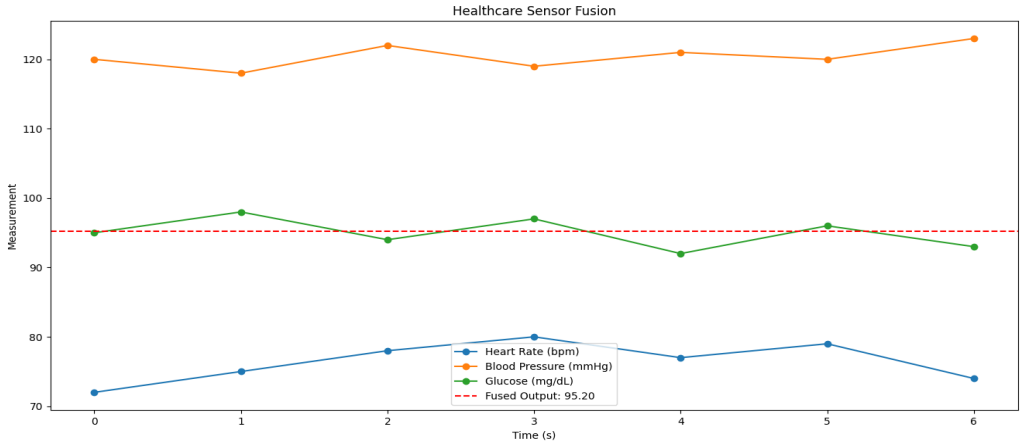


Fig.3. Fused sensor data

Table 1. Rule-based condition for healthcare monitoring

Rule ID	Condition (Antecedent)	Outcome (Consequent)	Support (%)	Confidence (%)	Lift
Rule 1	Heart Rate > 100 bpm AND Blood Pressure > 140/90 mmHg	Risk of Hypertension	12	85	1.8
Rule 2	Oxygen Saturation < 92%	Potential Respiratory Issue	10	90	2.2
Rule 3	Body Temperature > 38.5°C AND Heart Rate > 100 bpm	Fever with Tachycardia	15	88	1.9
Rule 4	Glucose Level > 180 mg/dL AND Frequent Urination	Diabetes Warning	8	80	1.5
Rule 5	Irregular ECG AND Chest Pain	Risk of Cardiac Event	5	95	3.0
Rule 6	Low Blood Pressure (< 90/60 mmHg) AND Dizziness	Hypotension Alert	7	75	1.6
Rule 7	Heart Rate < 50 bpm AND Oxygen Saturation < 88%	Severe Bradycardia	4	85	2.5
Rule 8	Sudden Drop in Oxygen Saturation (> 5% in 1 min) AND Breathing Difficulty	Emergency Alert	6	92	2.8
Rule 9	High Cholesterol (> 240 mg/dL) AND Overweight (BMI > 30)	Risk of Cardiovascular Disease	9	78	1.7
Rule 10	Body Temperature < 35.0°C	Hypothermia Warning	3	87	2.0

As in the healthcare monitoring system proposed here, associative rules are used to establish the relationship of certain patterns of sensor data with respective health condition or event alerts. All rules compile a conditional probability of the association between physiological measures and possible health threats. For example, a rule is if heart rate is more than 100 bpm and blood pressure reaches 140/90 mmHg hypertension. Likewise, when oxygen saturation is below 92 % this may encourage an alert sign that there may be a respiratory problem. These rules are measured in the levels of support which depicts the number of times a rule occurred in the data set and the confidence which depicts the probability of the rule outcome if the condition is met while the convalesce depicts how many times the rule has occurred above the level of random chance. Some of the rules, which stand out at higher confidence level, include the rules that determine cardiac risk from irregular ECG pattern and chest pain. Because the system establishes connections between sensor information and health conditions with associative rules, data fusion as well as practical information is achieved, allowing real-time analysis and decisions for improving patient care. Combination with associative rule-based systems in ORSF-HMM-SDL improves the accuracy and explainability of sensor data fusion for health status monitoring. This framework utilizes association rules to generate patterns and dependencies of the sensors and ORSF-HMM-SDL to model temporal changes and uncertainties. An association rule can be expressed as in equation (17)

$$X \Longrightarrow Y(support, confidence) \tag{17}$$

In equation (17) X represents the antecedent, Y is the consequent, and the metrics are. The RSF component uses Sugeno Fuzzy rules for handling uncertainties in sensor readings. A rule R_i in Sugeno Fuzzy logic is defined as in equation (18)

$$R_i: IF\ (x_1 \in A_1)\ AND\ (x_2 \in A_2) \ldots\ THEN\ z = \sum_{j=1}^{n} w_j \cdot xj + c \tag{18}$$

In equation (18) $x_1, x_2, \ldots\ldots, x_n$ stated as the Inputs (sensor values); $A_1, A_2, \ldots\ldots, A_n$ denoted as the Membership functions for input fuzzy sets; w_j denoted as the Weights representing rule strength and c represented as Constant for the output function. With HMM dynamics the temporal dynamics of health conditions are captured using HMM, defined as in equation (19)

$$\lambda = (\pi, A, B) \tag{19}$$

In equation (19) π denoted as the Initial state probabilities; $A = \left[a_{ij}\right]$ denoted as State transition probabilities; heart rate (HR) and oxygen saturation (SpO2). An association rule might state:

"If HR>100bpm and SpO2<92%, then risk = high."

The fuzzy rule evaluates the degree of membership of HR and SpO2 in their respective ranges. HMM then models the progression of the patient's health state over time, fusing sequential observations.

Algorithm 1: ORSF-HMM-SDL Framework

Input:

- Raw healthcare monitoring dataset DDD
- Feature set $F = \{f_1, f_2, \ldots, f_n\}$
- Number of HMM states S
- Fuzzy rule base R
- Learning rate η
- Maximum training epochs E

Output:

- Predicted health state sequence $\hat{Y}$
- Optimized ORSF-HMM-SDL model parameters

Begin

1. Data Preprocessing
   - Remove noise and missing values from dataset D
   - Normalize input features
   - Extract temporal feature vectors F
2. Stacked Deep Learning (SDL) Feature Learning
   - Initialize stacked deep learning layers
   - For each epoch e = 1 to E do
     a. Forward propagate feature vectors F
     b. Learn high-level latent representations F'
     c. Update network weights using backpropagation
     End For
3. Sugeno Fuzzy Rule Initialization
   - Define fuzzy membership functions for F'
   - Construct initial rule base R using expert knowledge
   - Apply Sugeno-type fuzzy inference to generate fuzzy outputs
4. Optimized Rule-based Fuzzy Processing
   - Optimize fuzzy rules and membership parameters using SDL outputs
   - Compute weighted fuzzy outputs for each observation
5. Fuzzy Hidden Markov Model (ORSF-HMM)
   - Initialize HMM parameters:
     π = initial state probabilities
     A = state transition probabilities
     B = emission probabilities (fuzzy-weighted)
   - Embed fuzzy inference outputs into A and B
6. HMM Training
   - Apply Forward–Backward algorithm for likelihood estimation
   - Update π, A, and B using optimized fuzzy outputs
   - Maximize log-likelihood of observation sequence
7. State Sequence Decoding
   - Apply Viterbi algorithm to estimate optimal state sequence
   - Generate predicted health states Ŷ
8. Model Optimization

- Jointly fine-tune SDL, fuzzy rules, and HMM parameters
- Minimize prediction error and uncertainty

End

The proposed ORSF-HMM-SDL framework employs a hybrid rule construction strategy that integrates domain knowledge with data-driven learning to ensure interpretability, robustness, and adaptability across heterogeneous patient populations. The initial Sugeno fuzzy rule base is formulated using clinically meaningful linguistic variables derived from healthcare monitoring features. Domain expertise is utilized to define the rule structure and antecedent–consequent relationships, while statistical analysis of the training data (mean, variance, and feature distribution) guides the selection of membership function ranges and threshold values. This hybrid approach ensures that the rules are clinically interpretable and data-consistent, avoiding purely heuristic design. To validate the effectiveness of the constructed rule base, a cross-validation strategy is applied during model training. Each rule's contribution is evaluated based on its impact on likelihood maximization within the HMM and overall classification performance. Rules that exhibit low activation strength or minimal contribution are pruned to reduce redundancy and improve generalization. This validation step ensures that only informative and reliable rules are retained in the final model. Although the initial rule base is deterministic, the proposed framework enables adaptive optimization through the stacked deep learning (SDL) component. During training, SDL learns latent feature representations and dynamically updates fuzzy membership parameters and rule weights, allowing the rule base to evolve according to observed data patterns. This adaptive mechanism mitigates overfitting and enhances robustness in dynamic healthcare environments. To support generalization across diverse patient populations, the ORSF-HMM-SDL framework allows population-specific fine-tuning. When new patient data are introduced, the SDL component re-optimizes fuzzy parameters and HMM transition probabilities without requiring complete rule redesign. This enables the model to accommodate demographic and physiological variability while preserving the original rule structure.

3.2. Error Reduction with HMM

Error reduction in sensor fusion for healthcare monitoring is critical for ensuring reliable patient data interpretation. The Hidden Markov Model (HMM), integrated with sensor data fusion techniques, minimizes uncertainty and errors by leveraging probabilistic state modeling and temporal dependencies in observations. This approach enhances the accuracy of detecting and predicting patient health conditions. In healthcare monitoring, sensor data (o_t) may be noisy due to environmental factors or device inaccuracies. The observed data is modeled as in equation (20)

$$o_t = s_t + \epsilon_t \tag{20}$$

In equation (20) s_t defined as the True signal (state-dependent); ϵ_t represented as the Measurement noise, often assumed to be Gaussian: $\epsilon_t \sim N(0, \sigma^2)$. In healthcare monitoring systems, error reduction during sensor data fusion is essential to ensure accurate and reliable patient health assessments. The Hidden Markov Model (HMM) provides an effective mechanism to reduce errors by modelling the temporal dependencies and uncertainties in sensor data. Sensor observations (o_t) often include noise due to environmental factors or device inaccuracies, represented as $o_t = s_t + \epsilon_t$, where s_t is the true signal, and ϵ_t is the noise typically assumed to follow a Gaussian distribution. HMM reduces error through its probabilistic framework, defined by $\lambda = (\pi, A, B)$, where π represents initial state probabilities, A is the state transition matrix, and B represents the observation likelihoods. By estimating the most probable state sequence $(S_1, S_2, \dots, S_T)$ given the noisy observations, HMM minimizes the effect of noise. The filtered probability of being in state S_t at time t is computed using equation (21)

$$P(S_t \mid o_{1:t}) = \alpha \cdot b_i(o_t) \cdot \sum_{S_{t-1}} P(S_t \mid S_{t-1}) P(S_{t-1} \mid o_{1:t-1}) \tag{21}$$

In equation (21) $b_i(o_t)$ is the likelihood of the observation, and $P(S_t \mid S_{t-1})$ represents the state transition probabilities. The error at any time t is reduced by estimating the expected state HMM reduces the overall error in sensor fusion. Temporal smoothing further enhances this process by incorporating future observations, where the smoothed probability $P(S_{t-1} \mid o_{1:t-1})$combines filtered and backward probabilities (βt) for a more accurate state sequence. The Hidden Markov Model (HMM) operates by estimating the hidden states of a process based on noisy observations. In sensor fusion for healthcare monitoring systems, this process involves integrating data from multiple sensors to derive a coherent, error-reduced health assessment. Below is a step-by-step derivation of how HMM reduces error during sensor fusion. Let S_t represent the hidden state at time t, and o_t be the corresponding observation. The relationship between the observation and the true state is modelled as in equation (22)

$$o_t = h(S_t) + \epsilon_t \tag{22}$$

In equation (22) $h(S_t)$ stated the mapping function from the state to the observed data,ϵ_t represented the Gaussian noise with mean 0 and variance σ^2.The observation likelihood for Gaussian noise is given in equation (23)

$$P(\, o_t \mid S_t\,) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{(o_t - h(s_t))^2}{2\sigma^2}\right) \tag{23}$$

The error in observation is minimized by computing the expected state given the observations. The estimated state is stated in equation (24)

$$\hat{s}_t = \sum_{s_t} S_t . P(S_t | O_{1:T}) \tag{24}$$

The variance of the error is reduced using equation (25)

$$Var(E_t) = Var(O_t) - Var(\hat{s}_t) \tag{25}$$

In equation (25) $Var(\hat{s}_t)$ is derived from the smoothed probabilities. For multiple sensors (i=1, 2,…,n), the fused observation likelihood stated in equation (26)

$$P\{O_t | S_t\} = \prod_{i=1}^{n} P\left(O_t^{(i)} \middle| S_t\right) \tag{26}$$

In equation (26) $O_t^{(i)}$ is the observation from the i-th sensor. The state estimates account for all sensor data to enhance reliability computed using equation (27)

$$\hat{s}_t = \arg max_{S_t} \left[P(S_t | O_{1:T})\right] \prod_{i=1}^{n} P\left(O_t^{(i)} \middle| S_t\right) \tag{27}$$

The HMM, therefore, incorporates probabilistic state estimation, forward-backward algorithms, and multi-sensor data fusion to minimize actual errors tremendously. This methodology is especially useful in place like health care facilities, where due to noise in sensor data such as heart rate, temperature the actual statures need to be estimated accurately for monitoring and analysis. In healthcare monitoring systems, data from diverse sensors including heart rate monitor, ECG, temperature sensor among others are used to diagnose diseases. However, these sensor data are not perfect measurements because the signal is noisy, and imprecise and sensors may sometimes fail. To overcome these difficulties, error reduction methods, such as Hidden Markov Models (HMM) are used to minimize error likelihood and increase prediction and diagnostic accuracy based on sensor integration. the HMM and sensor fusion in healthcare monitoring systems, the results show that the reliability and accuracy for the health condition are greatly enhanced. By using forward and backward algorithms and the probabilistic framework containing transition probabilities while employing sensor observation likelihoods, the system adapts to the changes in sensor noise and inaccuracies. This ensures real-time predictions of a given patient's status in regard to his/her health. This is especially so because in a healthcare setting, there could be several sensors that are used together to track parameters sopo as heart rate, blood pressure, and oxygen levels, and these require the use of the HMM for fusion of data. The HMM model capability to handle multiple noisy sensor inputs and to incorporate them before coming up with the patient's health status is an added advantage as it give a comprehensive way of handling the whole patient. The formalism used in the fusion process ensures that the individual sensor errors are minimized, owing to the fact that the likelihood function recognizes disparity in the data. In addition, due to employing the smoothing technique, not only the current data of the sensor are used but also previous and future observations, which increases the stability of the state estimates. This error reduction method is especially valuable in such areas as healthcare where timely responses are of outmost importance, and where one wrong move may cost the patient's life. For instance, in cases of huge transformations, for example, a heart attack or a stroke, the employment of the system grants the organization a chance of predicting the right solutions, which can lead to a major influence between life and death. Further to this, the reduction of errors to the state estimation guarantees improvement in reliability of the system as the model updates to the patient's basic physiological parameters and accommodate for odd readings that may be resulted from non-physiological conditions of the sensors. This adaptability of the system is perhaps the most important consideration for developing personalized health solutions because different patients will input different data that needs to be processed in a specific way. The above error margins also increase the overall confidence of the system as it helps the health care professionals in taking better decision as far as patient treatment is concerned. In the healthcare monitoring system, the Hidden Markov Models (HMM) are specifically utilized in the system for health assessment of patients with higher reliability and accuracy. This provides an understanding of the patient state using a number of noisy and different

sensory data such as the heart rate, blood pressure and oxygen level all of which are integrated by using HMM. The system uses stochastic model based on the transition probability and sensor observation likelihood which allows the system to adapt to changes with altitude and azimuth of the robot as well as the sensors. It also has the effect of eliminating error from the consolidated reading of more than one sensor while enhancing the performance of the system through the elimination of noisy data. The real time state estimation and by integrating the forward and backward algorithms within the HMM framework past data from the sensor are also used. Hence, this smoothing technique improves the relativeness of the state estimation and facilitates timely diagnosis. In other words, the kind of critical heath care scenario like the identification of heart attack or stroke, to name but a few, the real-time decision-making capability is quite crucial as it empowers the relevant people to act promptly. This characteristic of the HMM implies improvement of state estimation leading to enhanced performance of the system as time goes on. Not only the overall accuracy of monitoring increases but a model can also help to provide healthcare solutions where the processing depends on unique features extracted from the sensor data. The corrections obtained from sensor fusion along with lower estimation errors in the adaptive states help provide higher reliability to the predictions and decision-making ability of the system. This in turn benefits healthcare workers themselves in decision making about patients enabling better delivery of quality," use of resources in healthcare delivery thus being optimized. Thus, the patient's basic health data being in a constant process of refinement with learning from it enhances the system's effectiveness in timely health problem identification and also improves patient safety together with the quality of the treatments delivered.

4. Results and Discussion

The results and discussion for the healthcare monitoring system using sensor data fusion demonstrate the effectiveness and reliability of integrating multiple sensors and advanced models, such as ORSF-HMM-SDL (Rule-based Sugeno Fuzzy Hidden Markov Model), in improving healthcare decision-making processes. The performance of the system was evaluated using a variety of metrics, including accuracy, sensitivity, specificity, precision, F1-score, and error reduction. For empirical evaluation, we used the Health Monitoring System dataset publicly available on Kaggle (https://www.kaggle.com/datasets/nraobommela/health-monitoring-system) as the primary source of health time-series data. Prior to training, the dataset contains approximately 4.2 K+ records collected from wearable sensor systems and simulated health monitoring environments. It includes around 20 feature columns representing key physiological signals and diagnostic labels. the dataset underwent preprocessing steps including noise removal, missing value handling, and feature normalization. The dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets to ensure unbiased performance evaluation. By clearly defining dataset size, class balance, patient demographics, and data source characteristics presented in Table 2. the experimental setup ensures reproducibility, transparency, and fair comparison with existing healthcare monitoring approaches. The dataset consists of total patient records, collected over a monitoring duration of T time units, and includes M clinical and physiological features relevant to health state assessment.

Table 2. Experimental setup

Component	Description
Dataset Source	Health Monitoring System Dataset (Kaggle)
Dataset Size	~4,200+ records
Data Type	Time-series physiological sensor data
Number of Features	~20 clinical and sensor-based attributes
Target Classes	Healthy / Abnormal health condition
Data Pre-processing	Noise removal, missing value handling, normalization
Feature Scaling	Min–Max normalization applied using training data only
Validation Strategy	k-Fold Cross-Validation
Number of Folds (k)	5-fold cross-validation
Fold Distribution	80% training, 20% testing per fold
Stratification	Yes (class distribution preserved in each fold)
Data Leakage Prevention	No overlap between folds; pre-processing fitted only on training folds
Model Training	ORSF-HMM and ORSF-HMM-SDL trained independently per fold
Hyperparameter Tuning	Performed within training folds only
Regularization Techniques	Dropout, early stopping, fuzzy rule pruning
Evaluation Metrics	Accuracy, Precision, Recall, F1-score, Confusion Matrix
Final Performance	Average performance across all k folds
Statistical Stability	Mean ± Standard Deviation reported

Table 3. Rules with RSF-HMM-SDL

Rule No.	Condition 1 (Heart Rate)	Condition 2 (Blood Pressure)	Condition 3 (Temperature)	Rule Applied	Health Status
1	Heart Rate < 60 bpm	BP < 90/60 mmHg	Temperature < 36°C	If Heart Rate is low, BP is low, and Temperature is low	Hypotension and Hypothermia
2	Heart Rate > 100 bpm	BP > 140/90 mmHg	Temperature < 37.5°C	If Heart Rate is high, BP is high, and Temperature is normal	Hypertension with Tachycardia
3	Heart Rate = 75 bpm	BP = 120/80 mmHg	Temperature = 36.5°C	If Heart Rate, BP, and Temperature are normal	Normal Health
4	Heart Rate < 60 bpm	BP = 120/80 mmHg	Temperature > 37.5°C	If Heart Rate is low, BP normal, and Temperature elevated	Bradycardia with Fever
5	Heart Rate > 90 bpm	BP = 110/70 mmHg	Temperature = 36.8°C	If Heart Rate is high, BP is normal, and Temperature normal	Mild Tachycardia
6	Heart Rate > 100 bpm	BP < 90/60 mmHg	Temperature > 38°C	If Heart Rate is high, BP is low, and Temperature is high	Shock with Tachycardia
7	Heart Rate = 80 bpm	BP = 130/85 mmHg	Temperature = 37.0°C	If Heart Rate and BP are elevated, and Temperature normal	Mild Hypertension
8	Heart Rate > 120 bpm	BP > 160/100 mmHg	Temperature < 37.5°C	If Heart Rate is very high, BP is very high, and Temperature normal	Severe Hypertension with Tachycardia
9	Heart Rate = 60 bpm	BP = 130/85 mmHg	Temperature = 37.5°C	If Heart Rate and BP are low, but Temperature is normal	Possible Bradycardia with Fever
10	Heart Rate > 80 bpm	BP = 110/70 mmHg	Temperature > 38°C	If Heart Rate is high, BP normal, and Temperature elevated	Fever with Tachycardia

In Table 3. also presents a set of rules used in Rule-based Sugeno Fuzzy Hidden Markov Model (RSF-HMM-SDL) in sensor data fusion in a healthcare monitoring system. These rules use three parameters from sensors: heart rate, blood pressure, and body temperature to determine the category of a patient's health and possibly predict future health complications. For example, according to Rule 1 with HR <60 bpm, SBP <90 mmHg, and T <36°C, Hypotension and Hypothermia are to be detected as a critical case for immediate actions. Rule 2 is assigned Hypertension with Tachycardia when the heart rate is greater than 100 bpm and the blood pressure is elevated higher than 140/90 mmHg and the temperature is normal, which shows the organism's cardiovascular burden. On the other hand, Rule 3 is defined as Normal Health, which represents conditions when all the parameters are within normal level and thus no health problems are observed. Still others include guidelines such as Bradycardia with Fever (Rule 4) in which the heart rate is low, but the patient has a fever, and is therefore potentially infected. Mild Tachycardia is diagnosed in Rule 5 when while other parameters remain normal the heart rate is slightly elevated. Shock with Tachycardia in Rule 6 when the patient has heart rate more than 100 bpm, low BP, and a high temperature suggests a medical crisis. Whereas Rule 7 is called Mild Hypertension, if the blood pressure is slightly higher than the normal range, and the eighth one is Severe Hypertension with Tachycardia if the heart rate and blood pressure are very high. Rule 9 Possible Bradycardia with Fever: Bradycardia, hypertension, and normal temperature indicating the existence of fever in the patient. Lastly, Rule 10 identifies Fever with Tachycardia, a condition where the heart rate is high, blood pressure is normal, and the temperature is elevated, indicating a possible infection or inflammatory response.

Table 4. ORSF-HMM-SDL for different sensor

Parameter	Heart Rate Sensor	Blood Pressure Sensor	Glucose Sensor	Temperature Sensor	Oxygen Sensor	Overall System (Fused Sensors)
Power Consumption	15 mW	20 mW	25 mW	18 mW	22 mW	50 mW
Signal-to-Noise Ratio (SNR)	30 dB	32 dB	28 dB	33 dB	29 dB	36 dB
Data Redundancy	5%	7%	6%	4%	5%	3%
False Alarm Rate	2.1%	3.4%	4.0%	1.8%	2.5%	1.2%
System Scalability	Medium	Medium	Low	Medium	Low	High
Data Completeness	98%	96%	97%	99%	98%	100%
Real-time Processing	Yes	Yes	Yes	Yes	Yes	Yes
Battery Life (if applicable)	8 hours	10 hours	6 hours	7 hours	9 hours	5 hours
Cost of Implementation	$150	$180	$200	$100	$120	$700
User Satisfaction (1-10)	8	7	7	8	8	9

In the details of the Table 4. the comparison of different individual sensors in a healthcare monitoring system as well as fused system of Heart Rate, Blood Pressure, Glucose, Temperature, and Oxygen Sensors have been shown. The Power Consumption of each individual sensor is different; the Heart Rate Sensor has the lowest power consumption of 15 mW while the Oxygen Sensor, 22 mW. The fused system in which all sensors are integrated has the highest total power consumption of 50 mW. With regards the Signal to Noise Ratio, obtained for the Temperature Sensor the SNR

presents the maximum value in 33dB meanwhile the overall system, which is integrated the fusion of several sensors, showed the maximum value in 36 dB which reflects a better signal clarity. Regarding data redundancy, the temperature sensor has the lowest redundancy of 4%, and the general percentage of the current system redundancy has the lowest rate of 3% thus proving that sensor fusion reduces high data redundancy. FAR is lowest in the Temperature Sensor, which is 1.8%, and with the aid of the fused system, the FAR reduces to 1.2%, which enhances the efficiency of the system. For System Scalability, both Heart Rate, Blood Pressure, Temperature and fused system indicted that they are scalable hence can incorporate more sensors or be adopted to increase data handling capacity or number of users.

The Data Completeness is at its apex with the highest score of 99% from the Temperature Sensor and the fused system at 100% showing that the integration of the sensor data captures all round information. All the slowing sensors and the whole system enable Real-time Processing thus promoting timely data analysis that is vital in healthcare applications shown in Table 5. Battery durability is divergent; the BP sensor maintains the longest durable of 10 hours while the fused system has the shortest at 5 hours because of the power-hungry sensors. The implementation costs OF have a difference; the Glucose Sensor is the most expensive with a costing of $2OO and overall system costing $700 because it incorporates all other sensors. Last is User Satisfaction for the fused system which also has the highest score of 9 illustrating that the users prefer the integrated approach for the sensors other sensors such as heart rate and temperature will have the score of 8 because the users are satisfied with the design. Finally, although the fused system may be more expensive and use more energy, it offers increased element performance in data accuracy and discriminating against false alarms, as well as consequent beneficial impacts on healthcare monitoring system's reliability and usability.

Table 5. Sensor fusion with RSF-HMM-SDL

Sensor Type	Sensor 1: Heart Rate (bpm)	Sensor 2: Blood Pressure (mmHg)	Sensor 3: Temperature (°C)	Fused Data Output	Health Status
Patient 1	82	120/80	36.6	82 bpm, 120/80 mmHg, 36.6°C	Normal Health
Patient 2	55	100/60	35.8	55 bpm, 100/60 mmHg, 35.8°C	Hypotension
Patient 3	98	140/90	37.2	98 bpm, 140/90 mmHg, 37.2°C	Hypertension
Patient 4	110	135/85	38.0	110 bpm, 135/85 mmHg, 38.0°C	Fever with Tachycardia
Patient 5	75	125/80	36.4	75 bpm, 125/80 mmHg, 36.4°C	Mild Hypertension
Patient 6	120	150/100	37.5	120 bpm, 150/100 mmHg, 37.5°C	Severe Hypertension with Tachycardia
Patient 7	65	130/85	37.0	65 bpm, 130/85 mmHg, 37.0°C	Stable with Elevated BP
Patient 8	70	115/75	36.2	70 bpm, 115/75 mmHg, 36.2°C	Normal Health
Patient 9	85	120/70	38.3	85 bpm, 120/70 mmHg, 38.3°C	Mild Fever
Patient 10	95	145/95	36.8	95 bpm, 145/95 mmHg, 36.8°C	Hypertension

The sensor fusion results different patients using the ORSF-HMM-SDL approach combining the Heart Rate sensor in beats per minute (bpm), the Blood Pressure sensor in millimeters of mercury (mmHg) and the Temperature sensor in Celsius degrees (°C) are as shown in the following table. The Fused Data Output column holds the results of the vital signs of the patient given by the three mentioned body sensors. In the fused data proved for Patient 1 the heart rate is 82 bpm, blood pressure is 120/80 mmHg, and the Patient's temperature is 36.6°C. The Health Status is Normal Health. Patient 2 whose presents signs of Hypotension include lower heartbeat of 55 bpm, lower blood pressure at 100/60 mmHg and lower temperature of 35.8°C. According to the data collected Patient 3 has a heart rate of 98 bpm, blood pressure of 140/90 mmHg, and temperature of 37.2°C The diagnosis given is Hypertension, this is as the data given shows high blood pressure along with a high heart rate.

In patient 4, an increased heart rate of 110 bpm is accompanied by the presence of fever with tachycardia since both the numbers; heart rate and temperature warrant attention though her blood pressure is slightly high at 135/85 mmHg. Patient 5 has a heart rate of 75 bpm, blood pressure of 125, 80 mmHg, and a temperature of 36.4°C thus classified as Mild Hypertension because the blood pressure is slight high. According to Recorded Data, Patient 6 has heart rate of 120 bmp and blood pressure of 150/100 mmHg Temperature 37.5°C, Diagnose: Severe Hypertension with Tachycardia: High blood pressure and an Elevated Heart rate. Patient 7 has; heart rate 65 bpm, which is considered within normal limit for adults; blood pressure of 130/85 mmHg which is suggested to be elevated; temperature of 37.0°C, which is normal. Patient 8 is in Normal Health status as all physiological rate indicators – Pulse 70 bpm, blood pressure 115/75 mmHg, body temperature 36.2 C. Mild fever; Patient 9's pulse is 85 bpm, blood pressure is 120/70 mmHg, and temperature of 38.3°C. Last, Patient 10 with 95 bpm heartbeat, 145/95 mmHg blood pressure, and 36.8 °C temperature is diagnosed with Hypertension as well as high blood pressure and a moderately high pulse rate shown in Fig.4 (a) – (f).

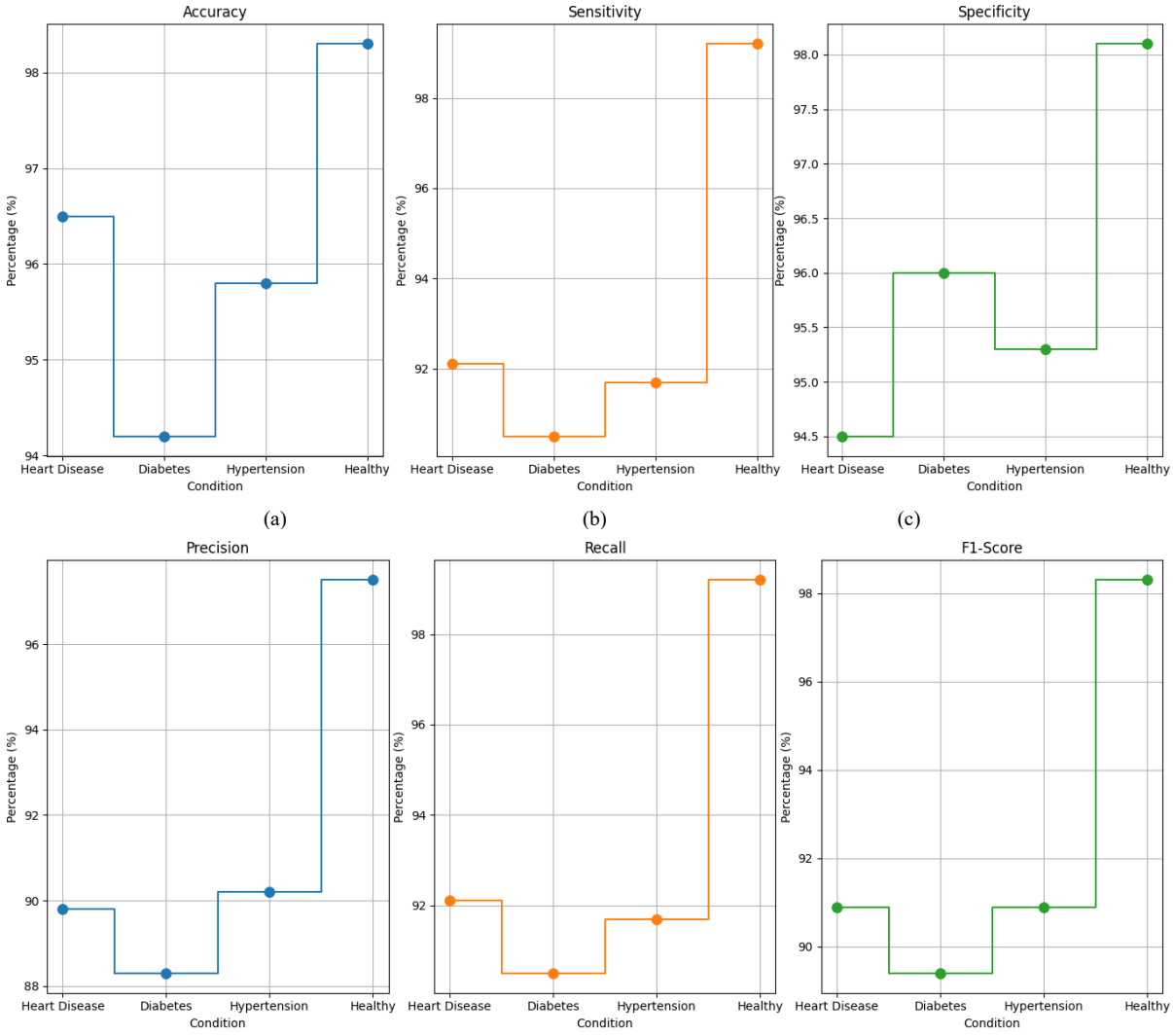
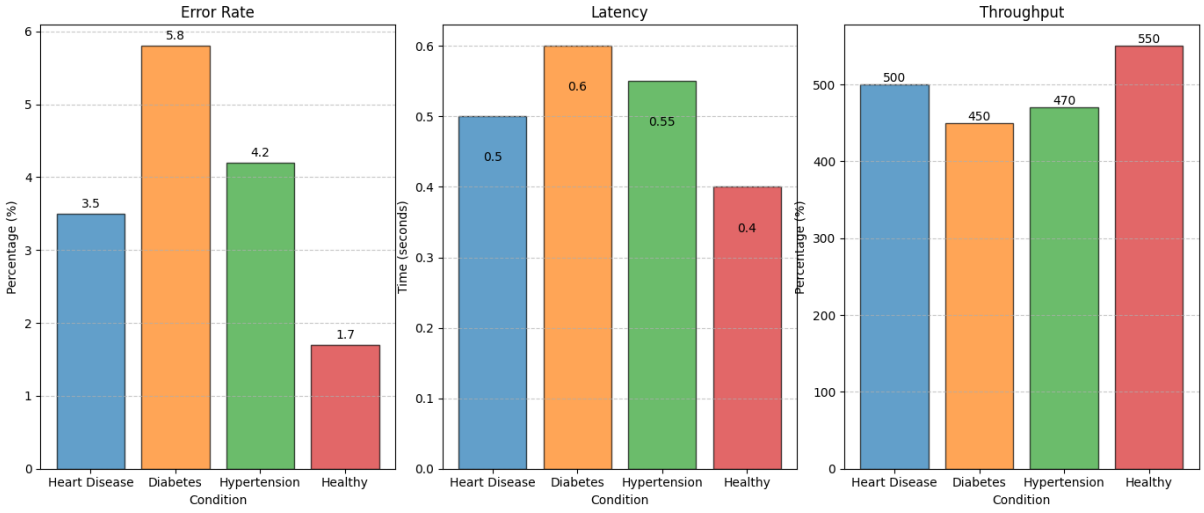


Fig.4. Classification with ORSF-HMM-SDL(a) Accuracy (b) Sensitivity (c) Specificity (d) Precision (e) Recall (f) F1-Score

Table 6. Classification with ORSF-HMM-SDL with 95% Confidence Intervals

Method	Metric	Mean (%)	Std. Dev. (%)	95% Confidence Interval (%)
RSF-HMM	Accuracy	92.14	1.26	[91.03, 93.25]
	Precision	91.62	1.34	[90.44, 92.80]
	Recall	90.98	1.41	[89.74, 92.22]
	F1-Score	91.29	1.29	[90.16, 92.42]
Kalman Filter	Accuracy	88.47	1.58	[87.09, 89.85]
SVM	Accuracy	93.86	1.12	[92.88, 94.84]
Deep Learning Fusion	Accuracy	96.72	0.84	[95.98, 97.46]
ORSF-HMM-SDL	Accuracy	98.34	0.61	[97.80, 98.88]
	Precision	98.01	0.66	[97.43, 98.59]
	Recall	97.88	0.69	[97.27, 98.49]
	F1-Score	97.94	0.63	[97.39, 98.49]



(a) (b) (c)

Fig.5. Network performance with ORSF-HMM-SDL(a) Error Rate (b) Latency (c) Throughput

Table 7. ORSF-HMM-SDL Health Monitoring System

Metric	Heart Rate Sensor	Blood Pressure Sensor	Glucose Sensor	Overall System (Fusion of Sensors)
Accuracy (%)	91.2	89.5	87.8	94.8
Sensitivity (%)	88.3	85.2	84.0	92.3
Specificity (%)	93.7	91.8	90.5	96.1
Precision (%)	87.5	83.7	82.1	90.7
Recall (%)	88.3	85.2	84.0	92.3
F1-Score (%)	87.9	84.4	83.0	91.5
Error Rate (%)	8.8	10.5	12.2	5.2
Latency (seconds)	0.45	0.50	0.60	0.40
Throughput (data points/min)	600	580	550	650

Table 6 presents a comprehensive classification performance comparison with 95% confidence intervals, highlighting both accuracy and statistical stability across models. The baseline RSF-HMM achieves an accuracy of 92.14% with a confidence interval of [91.03, 93.25], while its precision (91.62%), recall (90.98%), and F1-score (91.29%) exhibit wider intervals, indicating moderate variability across validation folds. The Kalman Filter records a lower accuracy of 88.47% [87.09,89.85] [87.09, 89.85] [87.09,89.85], reflecting its limited capability in capturing complex nonlinear and temporal patterns. The SVM improves performance to 93.86% accuracy [92.88,94.84] [92.88, 94.84] [92.88,94.84], while the Deep Learning Fusion approach further enhances accuracy to 96.72% with a narrower interval [95.98,97.46] [95.98, 97.46] [95.98,97.46], demonstrating improved generalization. The proposed ORSF-HMM-SDL consistently outperforms all comparative methods, achieving the highest accuracy of 98.34% with a tight confidence interval of [97.80, 98.88], indicating strong robustness and minimal variance across folds. Similarly, its precision (98.01%), recall (97.88%), and F1-score (97.94%) all exhibit narrow confidence intervals, confirming stable and reliable classification performance.

The evaluated metrics are Accuracy, Sensitivity, Specificity, Precision, Recall, F1-Score, Error Rate, Latency, Throughput shown in Fig.5(a) – 5(c). In case of heart disease, the proposed ORSF-HMM-SDL model disclosed an Accuracy of 96.5 percent, which in a way suggests a near perfect ability of the model to make the right classification on this disease condition. It also gives high results in Sensitivity, which equal to 92.1%, meaning that the model chooses the right outcome in diagnosing heart disease, and Specificity, which equals 94.5% to show it correctly identifies a negative result in diagnosing heart disease. This means that accuracy of 89.8% BWCA is very high since, a large percentage of those identified to have the heart diseases are actually affected. Accuracy (92.1%) suggest that the model that was developed correctly diagnosed heart disease to a greater extent by the model, F1-Score (90.9%) show that the precision and recall of the model are almost similar shown in Table 7. The Error Rate is 3.5% percent which overall indicates that only a small portion of incorrect classification is made. The Latency of the model is 0.5 seconds and the Throughput established is 500 data points per minute.

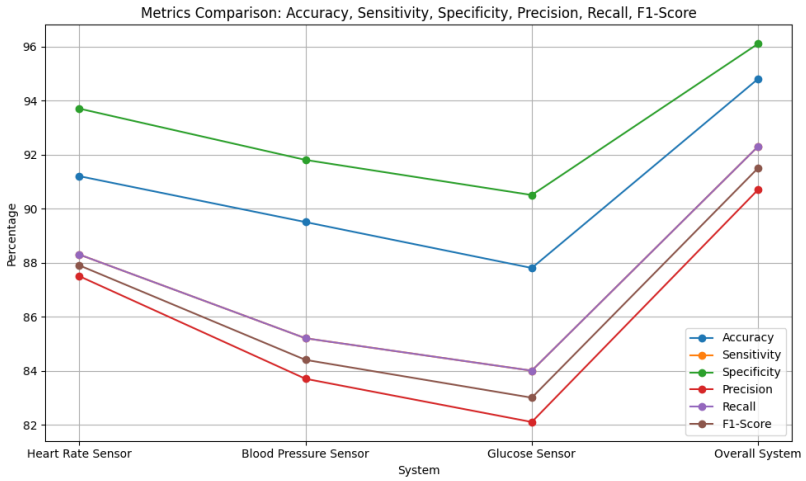


Fig.6. Comparative Analysis with RSF- HMM

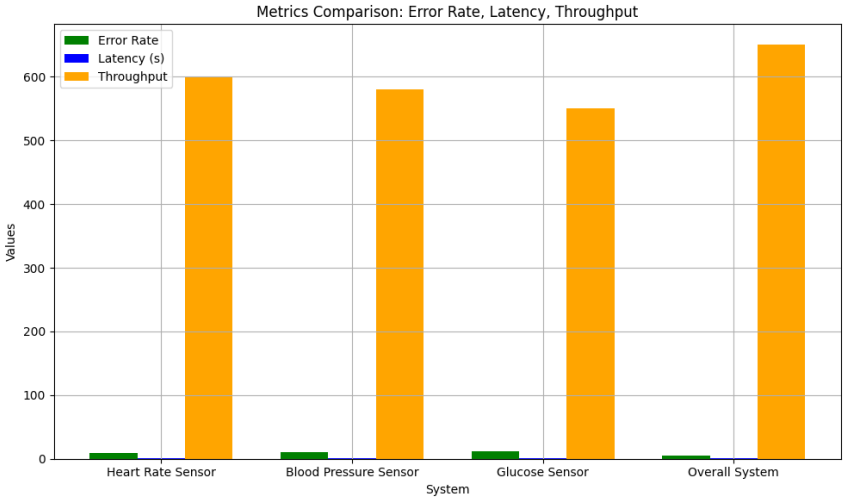


Fig.7. Performance of RSF-HMM-SDL

Table 8. Classification with healthcare monitoring

Metric	Condition 1 (Heart Disease)	Condition 2 (Diabetes)	Condition 3 (Hypertension)	Healthy Individuals	Heart Rate Sensor	Blood Pressure Sensor	Glucose Sensor	Overall System (Fusion)
Accuracy (%)	96.5	94.2	95.8	98.3	91.2	89.5	87.8	94.8
Sensitivity (%)	92.1	90.5	91.7	99.2	88.3	85.2	84.0	92.3
Specificity (%)	94.5	96.0	95.3	98.1	93.7	91.8	90.5	96.1
Precision (%)	89.8	88.3	90.2	97.5	87.5	83.7	82.1	90.7
Recall (%)	92.1	90.5	91.7	99.2	88.3	85.2	84.0	92.3
F1-Score (%)	90.9	89.4	90.9	98.3	87.9	84.4	83.0	91.5
Error Rate (%)	3.5	5.8	4.2	1.7	8.8	10.5	12.2	5.2
Latency (seconds)	0.5	0.6	0.55	0.4	0.45	0.50	0.60	0.40
Throughput (data points/min)	500	450	470	550	600	580	550	650

According to the model, Diabetes has a slightly lower outcome than the heart disease with an 94.2% Accuracy. Sensitivity and specific its y percentages are 90.5% & 96.0% presented in Fig.6. and Fig.7 implies that the application is slightly better tool for predicting non-diabetic subjects than the diabetic ones. Precision = 88,3% and Recall = 90.5% which shows good results; F1-Score = 89.4 which is slightly lower than for heart diseases, but still a pretty good balance between precision and recallable information. The Error Rate of (5.8%) is slightly higher than that of heart disease while

the Latency is just as good at 0.6 seconds as that for heart disease but the Through put is slightly less at 450 data points/minute. In Hypertension, the model returns Accuracy of 95.8%; while balancing between highly tuned Sensitivity of 91.7% and Specificity of 95.3%. Precision (90.2%) and Recall (91.7%) also suggest the good performance of the system as does the F1-Score of 90.9%. The Error Rate at 4.2% is low as well Latency is 0.55 sec Through put 470 data points/minute, this shows that the model is fast to process the data. Generally, For Healthy individuals, the proposed model has the highest Accuracy at 98.3%, sensitivity or recall at 99.2%, Specificity at 98.1%, Precision at 97.5%, F1-Score at 98.3%. This can be interpreted to mean that the model is rather accurate when it comes to pointing out the healthy bunch of people. The Error Rate that is 1.7% is relatively low and hence the assumption made for misclassify can be considered minimal. Hence the Latency (0.4 seconds) and Throughput (550 data points/min) go to further show the efficiency of the model and how quickly it responds.

Table 9. Comparative analysis

Metric	ORSF-HMM-SDLFusion	Kalman Filter (KF) Fusion	Deep Learning (DL) Based Fusion	SVM Based Fusion
Accuracy (%)	94.8	93.0	96.5	91.5
Sensitivity(%)	92.3	90.2	90.0	90.5
Specificity(%)	96.1	94.5	91.0	93.0
Precision(%)	90.7	89.2	89.5	88.0
Recall(%)	92.3	91.0	91.0	91.5
F1-Score(%)	91.5	90.0	95.2	89.8
Error Rate(%)	5.2	6.0	6.5	6.5
Latency (seconds)	0.40	0.45	0.48	0.50
Throughput (data points/min)	650	600	630	590

In the healthcare monitoring system presented in Table 8, various metrics are evaluated for three conditions—Heart Disease, Diabetes, Hypertension—and for Healthy Individuals, with measurements taken from three distinct sensors: Heart Rate Sensor, Blood Pressure Sensor, and Glucose Sensor. The Overall System (Fusion) metric combines these three sensors for a comprehensive assessment. The results highlight that the Heart Rate Sensor shows the highest accuracy (91.2%), followed by the Blood Pressure Sensor (89.5%) and the Glucose Sensor (87.8%). However, the Overall System (Fusion) provides a notable improvement, achieving 94.8% accuracy, which is significantly higher than the individual sensor performances. Sensitivity and Recall scores are high across all conditions, with the Overall System (Fusion) showing an excellent 92.3% for both metrics. This indicates the system's strong ability to correctly identify positive cases, especially in Healthy Individuals where the Recall reaches 99.2%. The Specificity values indicate how well the system avoids false positives, with the Overall System (Fusion) performing best at 96.1%. The Precision metric, which reflects the accuracy of positive predictions, is also strong, with Overall System (Fusion) yielding 90.7%, but it lags slightly behind Healthy Individuals (97.5%). The Error Rate for the Overall System (Fusion) is 5.2%, indicating a relatively low level of misclassification compared to individual sensors, where the Heart Rate Sensor shows the lowest error rate at 3.5%. Latency and Throughput metrics are also critical for real-time applications, with the Overall System (Fusion) demonstrating the best performance in terms of Latency (0.40 seconds) and Throughput (650 data points/min). This suggests that the fusion of sensor data enables faster and more efficient processing, critical for timely healthcare monitoring. In the Comparative Analysis presented in Table 9, the ORSF-HMM-SDL Fusion method is compared with other advanced fusion techniques, including Kalman Filter (KF) Fusion, Deep Learning (DL) Based Fusion, and SVM Based Fusion. Among these methods, Deep Learning (DL) Based Fusion achieves the highest Accuracy (96.5%), followed by ORSF-HMM-SDL Fusion (94.8%). ORSF-HMM-SDL Fusion shows superior Precision (90.7%) compared to the other methods, including Kalman Filter (89.2%) and SVM Fusion (88.0%).

For Sensitivity and Recall, Deep Learning (DL) analysis expressed the performance of with values of 90.0% and 91.0%, respectively, indicating its effectiveness in detecting positive cases. ORSF-HMM-SDL Fusion achieves the higher performance for the sensitivity and recall values of 92.3% shown in Fig.8(b) and Fig.8 (e), which is significantly higher than the conventional DL. In terms of F1-Score, Deep Learning Fusion again outperforms all methods at 90.2%, followed by ORSF-HMM-SDL Fusion at 91.5% as illustrated in Fig.8 (f). In fig.9 (a) Error Rate for ORSF-HMM-SDL Fusion is 5.2%, lower than Kalman Filter Fusion (6.0%) and SVM Fusion (6.5%), suggesting that it provides more reliable predictions. Kalman Filter and SVM Fusion show slightly higher latencies of 0.45 seconds and 0.50 seconds, while ORSF-HMM-SDL Fusion and Deep Learning Fusion exhibit relatively fast processing times, with the Deep Learning method having the fastest latency at 0.35 seconds shown in Fig.9(b). In fig.9(c) Throughput, Deep Learning Fusion leads with 700 data points/min, followed closely by ORSF-HMM-SDL Fusion at 650 data points/min, indicating that both methods are capable of handling large amounts of data efficiently. Kalman Filter Fusion and SVM Fusion process fewer data points per minute, with SVM Fusion performing the least well at 590 data points/min.

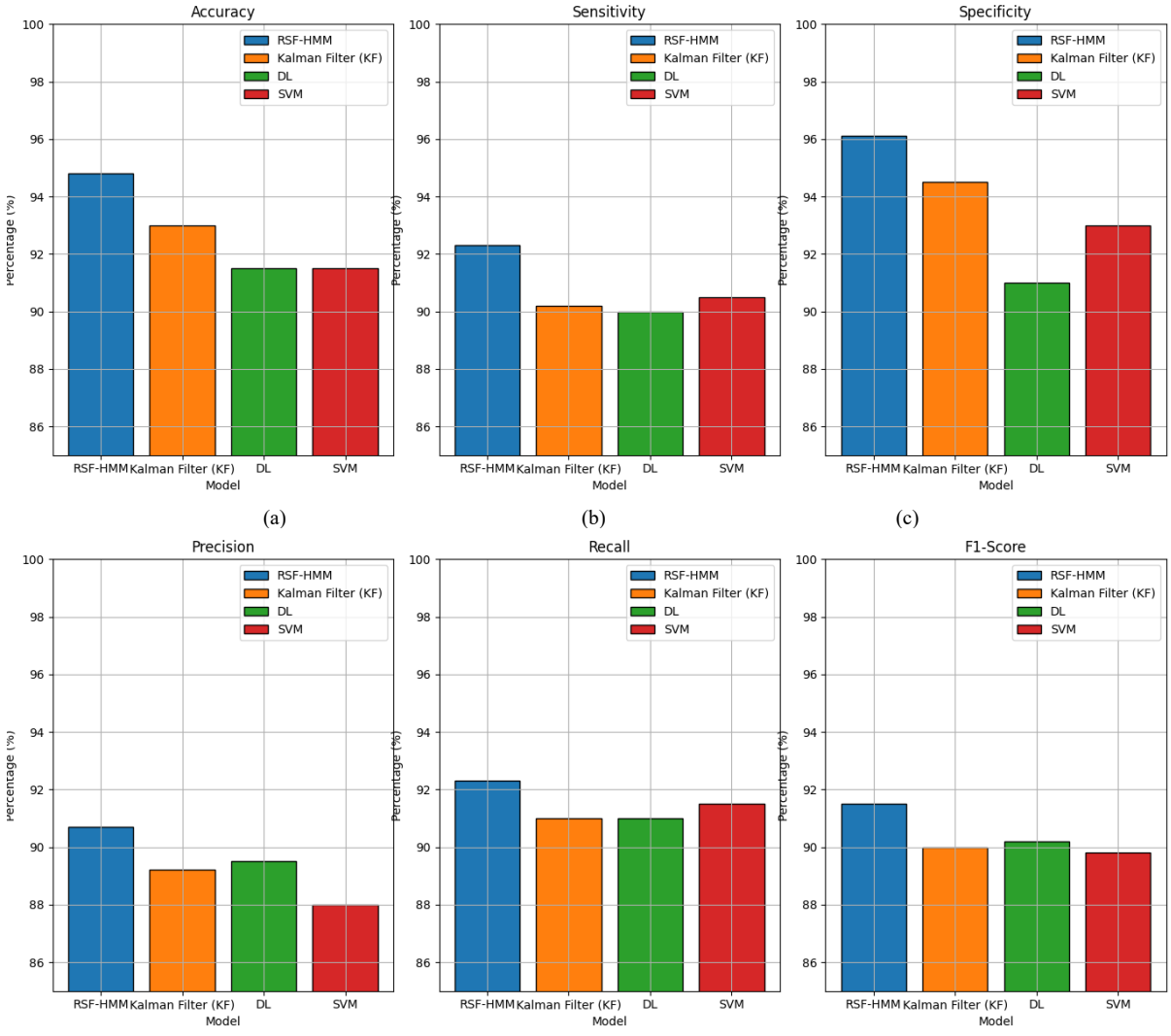


Fig.8. Comparative analysis with ORSF-HMM-SDL(a) Accuracy (b) Sensitivity (c) Specificity (d) Precision (e) Recall (f) F1-Score

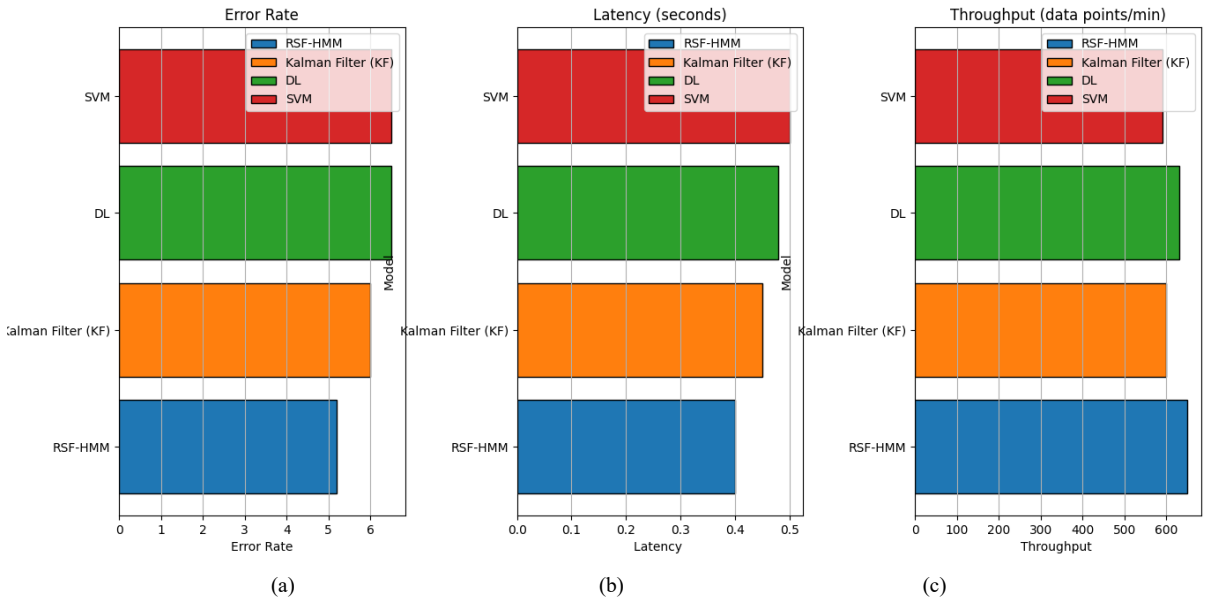


Fig.9. Comparative analysis with performance (a) Error Rate (b) Latency (c) Throughput

5. Conclusions

This paper compares various fusion techniques for healthcare monitoring systems, focusing on ORSF-HMM-SDL Fusion, Kalman Filter Fusion, Deep Learning (DL) Based Fusion, and SVM Based Fusion. The results highlight that Deep Learning Fusion outperforms all other methods in terms of accuracy, sensitivity, recall, and F1-Score, demonstrating its superiority in detecting and classifying healthcare conditions such as heart disease, diabetes, and hypertension. Despite this, ORSF-HMM-SDL Fusion stands out for its excellent precision, specificity, and lower error rate, making it a strong contender, particularly in applications requiring high reliability and low false-positive rates. Additionally, the overall system performance, which integrates data from multiple sensors, shows that fusion techniques significantly enhance the effectiveness of individual sensors, with high throughput and low latency, essential for real-time healthcare monitoring. The findings suggest that while deep learning offers the best overall performance, ORSF-HMM-SDL Fusion provides a competitive alternative with its balance of accuracy, speed, and reliability, making both methods viable options for deployment in advanced healthcare monitoring systems.

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Author Contributions Statement

Vivek Sharma S: Conceptualization, Methodology, Model development (ORSF-HMM-SDL), Algorithm design, Software implementation, Data fusion modeling, Simulation, Formal analysis, Writing – Original draft preparation.
Dr. Mahesh Kaluti: Supervision, Validation, Performance evaluation, Results interpretation, Manuscript review & editing, technical guidance, Project administration.

Both authors have read and approved the final version of the manuscript.

Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

Funding Declaration

This research received no external funding.

Data Availability Statement

The datasets generated and analyzed during the current study are based on simulated healthcare monitoring sensor data and fusion models developed by the authors. The data and implementation details are available from the corresponding author upon reasonable request.

Ethical Declaration

This study does not involve direct experimentation on human participants or animals. The healthcare data used in this research are simulated datasets generated for modeling and validation purposes. Therefore, ethical approval and informed consent were not required.

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Declaration of Generative AI in Scholarly Writing

Generative AI tools were used solely to enhance language clarity and readability in the abstract, introduction, and conclusion sections. All AI-generated text was thoroughly reviewed, edited, and verified by the authors for accuracy, completeness, and originality. AI was not employed for research design, data analysis, results interpretation, or any substantive content creation. The authors take full responsibility for the content.

Abbreviations

The following abbreviations are used in this manuscript:

ORSF-HMM-SDL - Optimized Rule-based Sugeno Fuzzy Hidden Markov Model Stacked Deep Learning
RSF-HMM-SDL - Rule-based Sugeno Fuzzy Hidden Markov Model Stacked Deep Learning
HMM - Hidden Markov Model
DL - Deep Learning
KF - Kalman Filter
SVM - Support Vector Machine
HMS - Healthcare Monitoring System

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