Enhancing Diabetes Management: A Hybrid Adaptive Machine Learning Approach for Intelligent Patient Monitoring in e-Health Systems

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Abstract*—The goal of the present research is to better understand the need of accurate and ongoing monitoring in the complicated chronic metabolic disease known as diabetes. With the integration of an intelligent system utilising a hybrid adaptive machine learning classifier, the suggested method presents a novel way to tracking individuals with diabetes. The system uses cutting edge technologies like intelligent tracking and machine learning (ML) to improve the efficacy and accuracy of diabetes patient monitoring. Integrating smart gadgets, sensors, and telephones in key locations to gather full body dimension data that is essential for diabetic health forms the architectural basis. Using a dataset that includes comprehensive data on the patient's characteristics and glucose levels, this investigation looks at sixty-two diabetic patients who were followed up on a daily basis for sixty-seven days. The study presents a hybrid architecture that combines a Convolutional Neural Network (CNN) with a Support Vector Machine (SVM) in order to optimise system performance. To train and optimise the hybrid model, Grey Wolf Optimisation (GWO) is utilised, drawing inspiration from collaborative optimisation in wolf packs. Thorough assessment, utilising standardised performance criteria including recall, F1-Score, accuracy, precision, and the Receiver Operating Characteristic (ROC) Curve, methodically verifies the suggested solution. The results reveal a remarkable 99.6% accuracy rate, which shows a considerable increase throughout training epochs. The CNN-SVM hybrid model achieves a classification accuracy advantage of around 4.15% over traditional techniques such as SVM, Decision Trees, and Sequential Minimal Optimisation. Python software is used to implement the suggested CNN-SVM technique. This research advances e-health systems by presenting a novel framework for effective diabetic patient monitoring that integrates machine learning, intelligent tracking, and optimisation techniques. The results point to a great deal of promise for the proposed method in the field of medicine, especially in the accurate diagnosis and follow-up of diabetic patients, which would provide opportunities for tailored and adaptable patient care.

***Keywords*—Diabetes; machine learning; convolutional neural network; support vector machine; grey wolf optimization; e-health systems**

I. INTRODUCTION

Over the past few decades, diabetes mellitus, frequently characterized to as diabetes, has become a major worldwide health concern due to its constantly rising predominance. Increased levels of glucose in the blood are a characteristic of this metabolic illness, which is brought on by either inadequate insulin synthesis or an inefficient utilization of insulin by the body. The World Health Organization (WHO) reports, that the rate of diabetes has been rapidly rising globally, making it one of the biggest public health issues of the twenty-first century. Diabetes affects a wide range of individuals worldwide, as evidenced by its epidemiology [1]. With approximately 463 million individuals identified with diabetes as of 2019, developed nations as well as developing ones are struggling with an increase in the number of instances of the disease. If current conditions continue, this number is expected to rise, reaching an astounding 700 million people by 2045. Inactive ways of life, inadequate nutrition, and a growing elderly population are all contributing participants to this trend, which emphasizes the critical requirement for efficient management and preventive actions [2]. Diabetes that goes untreated has serious repercussions that impact several organ systems and cause significant health issues. Long-term effects include renal failure, blindness, neuropathy, and cardiovascular disorders, all of which significantly decrease the standards of life as well as the life expectancies of those who are impacted. Furthermore, the financial impact of diabetes-related medical expenses and lost productivity is significant, creating new difficulties for healthcare systems throughout the world [3].

There are several interrelated causes that lead to the diabetes pandemic. With the introduction of diets excessive in fats that are unhealthy and sugars that are processed and a decrease in physical activity, industrialization and modifications to lifestyles have created an environment that encourages obesity that promotes the development of diabetes. An individual's risk to the illness is influenced by both environmental and genetic variables, which combine to determine the person's susceptibility. Furthermore, the growing incidence of diabetes is made worsened by differences in the availability of healthcare and education, especially for communities with limited resources. Diabetes is becoming more and more common, which has serious consequences for public health and necessitates an all-encompassing strategy [4]. The three main strategies for reducing the rise in diabetes are prevention via health education, lifestyle modifications, as well as early detection. In addition, technological developments including the development of sophisticated monitoring systems have the potential to improve diabetes care while promoting an anticipatory approach to healthcare [5]. To reduce the effects of diabetes and enhance the physical and mental well-being of millions of people globally, the international community needs to collaborate together to address the complex interactions between hereditary, environmental, and lifestyle variables [6].

The complex nature of managing diabetes, characterized by the requirement for continual surveillance and individualized treatment, highlights the necessity for sophisticated monitoring systems. Diabetes, in contrast to many other chronic illnesses, requires close monitoring of blood sugar levels, dietary habits, activity levels, and medication compliance. Diabetes has several facets that impose significant stress on patients and healthcare professionals equally [7]. As a result, there is a strong demand for innovative approaches that may expedite monitoring procedures, give real-time information, and enable faster treatments. Diabetes is a very unique disorder, with changes in medical condition and patient responses to therapy occurring on an individual basis. In order to customize treatment plans to the particular requirements of each patient, sophisticated monitoring systems are now essential [8]. Through the integration of adaptive learning technologies and sophisticated monitoring mechanisms, these systems are able to evaluate large datasets and identify specific trends, offering a more detailed knowledge of a patient's health trajectories. Enhancing therapeutic efficacy, reducing adverse reactions, and ultimately improving patient outcomes are all possible with this customized strategy [9].

Patient-centered care is an innovative approach that prioritizes giving individuals the tools required to take an active role in their own health management. Modern monitoring devices are essential to this change because they provide patients with immediate information on their lifestyle decisions and health parameters. These systems have the potential for motivating patients to follow treatment programs, make educated decisions, and establish up healthy habits by cultivating an environment of ownership and awareness [10]. Furthermore, the incorporation of easy-to-use interfaces and smartphone applications might promote a proactive and cooperative approach to diabetes management by facilitating effortless interaction between patients and medical professionals. By using sophisticated technologies to monitor diabetes proactively, complications may be avoided, and the financial strain of the disease may be reduced. Early intervention can be used to mitigate the frequency of serious illnesses and hospitalizations by promptly detecting abnormalities from normal health indicators [11]. Sophisticated monitoring systems help healthcare systems preserve revenue over the course of time through promoting preventative care and supporting continuous maintenance of health. In order to effectively manage the numerous obstacles presented by this complicated and widespread chronic illness, improved monitoring systems are becoming increasingly necessary as the number of cases of diabetes rises worldwide [12].

Significant progress has been made in the field of diabetes e-health systems, which use technology to improve the treatment of patients and management. These systems usually incorporate a range of technologies to monitor and assist people with diabetes in everyday activities, such as online platforms, wearable technology, and mobile applications. Numerous current systems concentrate on monitoring blood glucose levels, activity levels, and consumption habits in real-time. While wearable technology, such continuous glucose monitors (CGMs), offer a constant supply of physiological information, mobile applications frequently act as a central centre for data gathering and processing [13]. e-Health technologies have made it possible for diabetes patients to take advantage of telehealth services and remote monitoring, eliminating the distance between patients and healthcare professionals in geographically dispersed areas. Regular assessments and treatment plan modifications are made possible through telehealth conversations, which eliminate the need for several visits to the clinic. By facilitating more adaptable and dynamic diabetic treatment, this integration lowers the need for frequent visits to the clinic and increases patient participation.

The incompatibility of various e-health technologies and systems is one of the main disadvantages. Variations in information formats and requirements may prevent the effortless transfer of information between healthcare systems and devices, which could result in evaluations of an individual's health state that are either inaccurate or incomplete. Security and confidentiality of information are major problems in e-health systems because of the sensitive character of health data. Challenges including illegal entry, leaks of information, and insufficient encryption protections caused patient privacy at risk and might undermine users' confidence in these systems. Participation among users and commitment over time to monitoring methods remain issues in regardless of the capacities of e-health systems [14]. The apparent complexities of the systems, unease with wearable technology, or a lack of customized input that aligns with their specific health objectives can all lead to patients detaching from ongoing surveillance. Certain e-health systems could depend on standard algorithms that do not adequately take into consideration the range of diabetes appearances people with the disease can have. An approach that applies to all patients may fail to recognize smaller variations in how each patient reacts to therapy, which could result in undesirable outcomes for certain groups of patients. e-Health systems are effective at collecting physiological data, but they can still do better when it comes to incorporating behavioural data, including how anxiety or other lifestyle factors affect diabetic treatment [15]. Increasing the comprehension of every facet of the patient experience can result in more comprehensive and individualized treatments. Improving interoperability, enhancing privacy and security protocols, boosting user engagement with intuitive interfaces, and fine-tuning algorithms in order to accommodate a range of patient profiles are all necessary to overcome these constraints. The continued development of e-health systems shows possibilities for improving patient outcomes, optimizing diabetic treatment, and expanding the field of electronic health records as technology advances.

The complicated and constantly changing nature of diabetes is the motivating factor driving the integration of intelligent tracking and a hybrid adaptive machine learning classifier in diabetes treatment. Individualized patterns of blood glucose levels, choices regarding lifestyle, and treatment responses are characteristics of diabetes. The complex and changing health trajectories of individuals with diabetes are frequently difficult for traditional, static models to represent. The system attempts to give patients a more comprehensive and individualized approach to diabetes management by combining intelligent tracking, which continually records and customizes to changing patient behaviours, and a hybrid adaptive machine learning classifier, which can learn complicated patterns in large datasets [16]. The traditional standardized method of managing diabetes may not be able to adequately satisfy each patient's specific demands. The device can collect instantaneous information on a patient's activities, eating habits, and physiological reactions because of intelligent tracking systems. This is enhanced by the hybrid adaptive machine learning classifier, which gains knowledge from the recorded information, customizes its model to account for individual differences, and offers individualized recommendations. This combination maximizes the effectiveness of therapies and improves patient outcomes by facilitating the transition towards more individualized and focused treatment techniques.

Continuous monitoring helps significantly in the treatment of diabetes since it makes it possible to identify small variations in health indicators that might signal impending emergencies. Intelligent tracking is integrated to provide an uninterrupted supply of pertinent data, and the hybrid adaptive machine learning classifier is extremely skilled at identifying complex patterns linked to early indicators of health decline. For those with diabetes, this continuous surveillance and early intervention strategy may help avoid complications, lessen the need for emergency interventions, and enhance their general quality of life. The hybrid adaptive machine learning classifier is intended to address the difficulties caused by the intrinsic unpredictability in the initial responses of individuals with diabetes to dietary and medication modifications [17]. Conventional classifiers could have trouble adjusting to these differences, which would result in less than ideal efficiency. Because of its adaptive characteristics, the suggested classifier can adapt over time to the intrinsic variety in diabetes presentations. This flexibility is especially important for patients with chronic conditions like diabetes, whose health can be affected by a wide range of variables. In the area of e-health and diabetes care, the combination of intelligent tracking with a hybrid adaptive machine learning classifier is a newly developed and creative method. While discrete components like machine learning and intelligent tracking have been studied independently, integrating them into a unified framework which functions effectively when combined is a novel contribution. The system's capacity to dynamically adjust to each patient's unique profile, learn from changing information over time, and offer customized suggestions for successful diabetes control essentially makes this system exceptional. This strategy might contribute to the expanding area of customized medicine and raise the standards for digital health interventions for chronic illnesses.

The Key Contribution of the paper is given as follows:

- The research presents a unique hybrid architecture that combines a SVM with a CNN to monitor diabetic patients. By combining the attributes of both models which is SVM's outstanding binary categorization and CNN's feature extraction capabilities, improves diabetes prediction accuracy.
- An intelligent tracking mechanism is utilized to collects detailed body dimension information from diabetes patients using cellphones, sensors, and smart devices. Beyond typical monitoring techniques, this integrated strategy ensures a more comprehensive awareness of the patient's health and contributes to a more individualized approach to treatment.
- The employed Grey Wolf Optimization is based on cooperative optimization observed among wolf packs, to fine-tune the hybrid model. This optimization method improves the efficacy and effectiveness of the model, offering an innovative approach for fine-tuning parameters in machine learning systems that are inspired by nature.
- The suggested approach shows a significant increase in accuracy. CNN-SVM hybrid model exhibits improved classification accuracy when compared to established approaches such as SVM, Decision Trees, and Sequential Minimal Optimization. This indicates the model's potential for dependable diabetic patient monitoring.
- Machine Learning, optimization, and intelligent tracking approaches, contributed to the improvement of e-health systems. This strategy has a lot of potential to improve the accuracy and efficiency of diabetes patient monitoring. Modern technology combined with the enhanced performance of the suggested hybrid model is a significant addition to the field of healthcare informatics.

The rest of the section is organised as shown below. Section II illustrates literature works on e-health Systems. Section III gives the Problem Statement. Section IV covers the proposed technique for Monitoring and Tracking the Patients with Diabetes. Section V illustrates the performance measures and summarises the findings and compares the method's performance to previous techniques. Section VI summarises the conclusion and paves the way for future works.

II. Related Works

Individuals with diabetes who receive continuous medical attention often have a greater standard lifestyle than those who do not. Due to technology improvements, healthcare costs can be reduced by utilizing the Internet of Things. Both the advancement of intelligent devices and a growth in the total amount of software linked to the networks are necessary for addressing the demands of e-health applications. Therefore, the cellular network must be able to accommodate sophisticated medical applications which require outstanding energy consumption in order to accomplish these objectives. The study develops combined voting classifier that utilizes neural networks to effectively forecast patients' diabetes through online monitoring. Internet of Things gadgets is used in the study to track patient cases. IoT devices provide their information for smartphones during evaluating, and those devices transmit the information to the cloud, where categorization is done. The Python tool is used to run the simulation on the gathered observations. The results from the simulation demonstrate that, in comparison to current the most advanced combination models, the suggested strategy provides a higher prediction rate, precision, recall, and f-measure. However, for information to be provided from connected devices to the cloud, the suggested solution depends on the Internet operating without interruptions. Restrictions in internet access might possibly undermine the dependability of the projections by affecting the continuous monitoring capability [18].

Because type 2 diabetes has a significant condition of disease and significantly lowers the patient's standard of existence, using computerized instruments and data technologies to control illness has become common place due to the close connection between healthcare and the worldwide web. The study attempted to determine how well several e-health treatments, varying in length, may help individuals who have type 2 diabetes achieve controlling their glycemic levels. Researchers investigated for randomization managed studies describing various e-health interventions for glycemic management in individuals with type 2 diabetes. Individuals with type 2 diabetes mellitus satisfied the following participation requirements: (1) interventional duration $\geq$1 month; (2) findings HbA1c (%); and (4) randomization management using e-health based techniques. Cochrane techniques were employed to evaluate potential biases. Researchers performed the Bayesian network a meta-examination using R 4.1.2. The most efficient intervention periods were found to be $\leq$6 months, according to subgroup evaluations. Individuals with diabetes who have type 2 diabetes can benefit from improved glycemic management through all forms of e-health-based interventions. With an ideal intervention length of $\leq$6 months, SMS is a high-frequency signal, low-barrier technique that delivers the highest benefit in decreasing HbA1c. The research concepts administration procedures and characteristics of participants may add variability due to the numerous types and timings of e-health treatments included in the inclusion. The variety of approaches may make it more difficult to reach firm judgments on the efficacy of particular therapies [19].

Many of the advances that technology has enabled about for humankind have made even the most difficult things simpler. The development of science and technology has led to the widespread deployment of intelligent machines. Numerous sectors, including health care for the public, medicine, and healthcare, have seen advancements. The monitoring of wellness and various other tasks may now be done effectively, economically, and intelligently thanks to recent advancements in healthcare. This is made feasible in large part by wearables. Despite their compact design, these gadgets are equipped with potent medical sensors that enable the monitoring of users' health problems. As technology and medical science have advanced, wearables have been equipped with an increasing number of sensors for tracking a wide range of activities, such as blood oxygen levels, body temperatures, cardiovascular disease, and activity monitoring systems, among many others. These gadgets allow users to store the outcomes for future usage and can be linked to smartphones. The necessity of wearables in healthcare and their potential to transform medical systems in the future were covered in this study. A case study is given illustrating how wearables may benefit both physicians and patients. Potential applications and research problems are also included in this publication. However, because patient groups vary and wearable devices are different, the report may have difficulty generalizing its results. The general application of the offered findings is limited by the realization that wearable device performance and utilization could differ across various populations, medical conditions, and geographical areas [20].

Globally, an advancing population is one of the biggest healthcare challenges. Due to their increased risk of chronic illnesses, which raise healthcare costs, older individuals demand greater resources from the healthcare system. One of the major developments within healthcare technological advances is the creation and ongoing operation of e-health solutions, which provide patients with mobile services to support and improve their treatment according to monitoring certain physiological information. Healthcare technology has advanced greatly in the previous few decades in terms of size, velocity, accessibility, and connectivity. The fact that individuals are restricted to smart rooms and a bed equipped with monitoring devices is a significant disadvantage of contemporary e-health monitoring systems. Because chronic patients have accessibility, security, and adaptability difficulties, such surveillance is not common. Furthermore, attached to a patient's body health monitoring gadgets provide no evaluations or recommendations. This work presents a multi-agent-based approach to tracking health conditions that aims to enhance the procedure by gathering patient information, reasoning collectively, and suggesting actions to patients as well as physicians in a mobile setting. The paper presents a multi-agent-based system that is assessed using a case study. The findings demonstrate that the suggested approach offers elderly, chronic, and distant patients an effective way to monitor their health. Furthermore, by employing 5G technology, the suggested method works better than the current health system and enables prompt medical services for patients who live far away. However, when the suggested agent-based system is expanded to support enormous user bases or extensive medical networks, its efficacy can encounter difficulties. As the size grows, problems with resource use, communication costs, and system efficiency could become increasingly noticeable [21].

Diabetes is a chronic illness caused by the pancreas' inability to produce enough insulin or to shield the body from non-consumable substances. Diabetes patient health monitoring is a methodical approach that provides us with comprehensive health information on individuals with diabetes. Health observation platforms for diabetic patients are essential for monitoring their state, especially when using Internet of Things connected devices. In simple terms, diabetic patient monitoring platforms may screen individuals with diabetes and save certain health data, such as body temperature, blood pressure, and blood glucose levels. Because predictive analysis may assist diabetic individuals, their relatives, medical professionals, and clinical researchers in making decisions about the patient's medication considering the circumstances of their state, it is necessary for diabetes patients. The study explores future research using Artificial Intelligence algorithms and presents a novel framework for monitoring the health of diabetes patients. However, technological problems and fluctuations may affect the accuracy of the information gathered by IoT devices, such wearables and sensors. The dependability of health information may be impacted by variables such as sensor reliability, measurement, and possible interference with the signal, which might have an effect on the monitoring system's general reliability [22].

In anticipation of the coronavirus disease-19 epidemic, audio-based telemedicine services for consultations and prescription medications were initially implemented in Korea. This study looked at how telehealth services affected health-care usage and drug prescription trends in hypertensive and diabetic individuals. The claims information from the Health Insurance Evaluation and Assessment Services for 2019 to 2021 were utilized. The difference-in-difference technique was utilized to compare the impact of telehealth treatments on the subjects as well as control groups before and following the period of intervention. Individuals in the untreated category employed in-person outpatient treatment, whereas those in the actual category received combined telemedicine and in-person treatments. The study comprised hypertensive individuals and diabetic patients. Telehealth services were linked to a rise in appointments with physicians among hypertensive. Patients with hypertension had a reduction in hospitals and visits to emergency rooms. In addition, policy execution has led to a rise in the medication possession ratio and the percentage of suitable prescriptions among patients with diabetes and high blood pressure. The data indicate a link between telemedicine service implementation and enhanced habits in health care usage and drug prescription, indicating telemedicine's potential utility in chronic illness management. However, the results of the investigation may be unique to the Korean health care system and not immediately relevant to other nations with differing healthcare facilities, laws, and cultural settings. Factors such as regulations, consumer preferences, and healthcare professional practices might differ greatly between nations [23].

The literature review includes a range of subjects related to health monitoring systems, with a special emphasis on the treatment of diabetes patients and the use of technology to deliver healthcare more effectively. The first study uses Internet of Things devices to follow patient cases and offers an integrated voting classifier using neural networks for online diabetes monitoring. Although it shows better prediction rates, accuracy, recall, and F-measure than previous models, it also emphasizes possible limits by pointing out that data transfer to the cloud depends on continuous internet availability. The efficacy of E-Health treatments for glycaemic control in type 2 diabetes is investigated in the second research, which highlights the advantages of brief intervention durations particularly less than six months and the usefulness of SMS in lowering HbA1c levels. In discussing wearables' revolutionary potential in the healthcare industry, the third piece of literature focuses on how intelligently they can monitor a range of health indicators. The study does, however, recognize that demographic heterogeneity and device variety make it difficult to generalize outcomes. The fourth research addresses the healthcare requirements of the aging population by suggesting a multi-agent-based health monitoring system that provides enhanced services and mobility for chronic patients. Finally, the fifth research highlights the use of artificial intelligence algorithms for predictive modelling in the introduction of an Internet of Things-based health monitoring system for patients with diabetes. There are still issues with scalability and data dependability, despite encouraging developments. Together, these studies demonstrate the potential advantages of integrating technology into healthcare, but they also emphasize the necessity of resolving related issues in order to achieve widespread acceptance and effectiveness.

III. Problem Statement

The present techniques used to monitor diabetic patients in electronic health systems frequently encounter issues such imprecise data analysis, restricted flexibility to accommodate different patient profiles, and inadequate real-time tracking capacity. By creating an advanced e-health System with an Integrated Intelligent Tracking Mechanism utilizing a Hybrid adaptive machine learning Classifier—more precisely, the suggested CNN-SVM model—this research seeks to address these problems. Accurate and individualized monitoring has been impeded by the present limitations in conventional approaches, which include their reliance on static thresholds and unsophisticated machine learning algorithms [6]. By combining the advantages of SVM for classification and CNN for feature extraction, the suggested CNN-SVM model outperforms other approaches in terms of robustness and efficiency when handling dynamic, complex patient information.

IV. Proposed Hybrid Adaptive Machine Learning Classifier

The methodology used in the research is an exhaustive approach to creating a sophisticated e-health system for tracking diabetic patients, combining sophisticated surveillance techniques with an integrated adaptable machine learning classifier. The dataset includes information from sixty-seven consecutive days of exams for sixty-two diabetic patients, of which forty-four were male and eighteen were female. Using Min-Max normalization as a preprocessing step, the 13,173 concentrations of glucose information points and five attributes are scaled uniformly. PCA is used in feature extraction to reduce dimensionality and find important factors that influence patient features and fluctuations in glucose levels. The categorization and tracking mechanism, which uses a hybrid convolutional neural network integrated with a support vector machine, is the central component of the suggested system. Seven layers of CNN automatically identify important characteristics, while SVM guarantees robust categorization. The paper presents an innovative Hybrid CNN-SVM framework and demonstrates how SVM's competence in binary categorization and CNN's extraction of characteristics capabilities complement each other. Modelling parameter tuning is done using the Grey Wolf Optimization framework, which takes its information from the cooperative optimization procedure utilized by wolf packs. This optimization, inspired by nature, improves the model's efficiency. Fig. 1 depicts the general architecture of the suggested model.

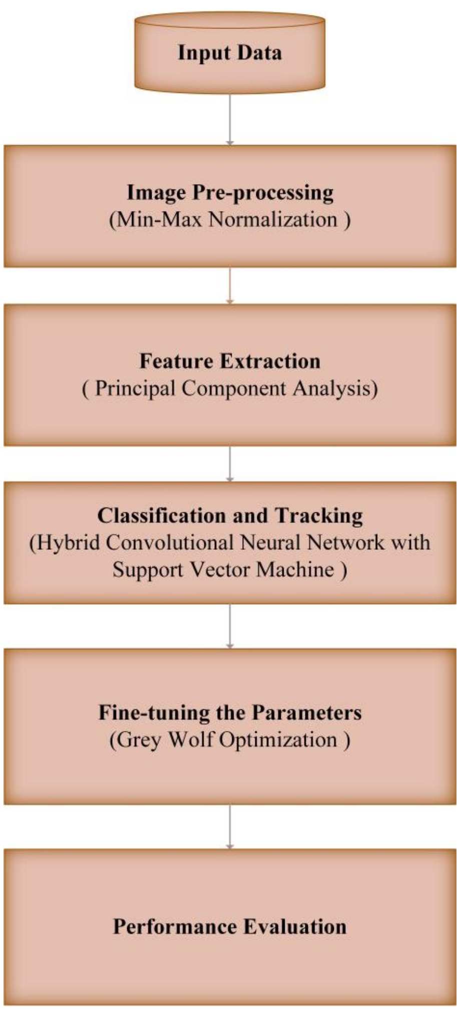

Fig. 1. Overall structure of the proposed model.

A. Data Collection

The sixty-two diabetic patients (forty-four men and eighteen women) whose medical histories required an average of sixty-seven days of testing were added to the database for this study. There are five characteristics and 13,173 glucose concentration information points in the glucose concentration sets [24].

B. Preprocessing using Min-Max Normalization

Standardized scaling of characteristics was ensured by applying Min-Max normalization throughout the preparation of the dataset. 13,173 glucose concentration information points and five attributes are included in the collection of data. The level of glucose and other features were subjected to Min-Max normalization in order to scale the data within an acceptable range, usually [0, 1]. In order to enable more accurate and efficient modelling of diabetes-related variations and patterns within the information set, normalization is a crucial step in removing scale-related inefficiencies and verifying that each characteristic contributes proportionately to the study.

The research may scale the input information into an appropriate range by using Min-Max normalization, enabling a more rapid and precise evaluation. The relationships between the data sources are preserved without affecting the original information by making effort that all of the variables that are entered are transformed into a similar interval utilizing the normalization approach. The capacity of Min-Max normalization to maintain that connect between information points is one of its main advantages. This demonstrates that following normalization, the information's relative distribution and structure are still maintained. Preserving the fundamental patterns and correlations in the information is essential to accurately manage the elements influencing the projected values. Utilize Eq. (1) to illustrate the Min-Max normalizing method.

$$k = min_{new} + (max_{new} - min_{new}) * \left(\frac{k - min_r}{max_s - min_s}\right) \quad (1)$$

The starting measurement point is represented by $"k"$ in this equation, the requisite values for the standardized data are denoted by min_{new} andmax_{new}, and the maximum and minimum values are indicated by max_r andmin_r, respectively. The speed and effectiveness of Min-Max normalization are its key benefits when handling an extensive amount of information points.

C. Feature Extraction using Principal Component Analysis

An essential first step in evaluating high-dimensional datasets, like the diabetic patient monitoring dataset, is feature extraction. A common method for reducing dimensionality in information includes Principal Component Analysis, which tries to extract the most crucial information from the data being analyzed while removing less significant aspects. PCA can assist in determining the major factors that most influence changes in individual characteristics and glucose levels within the framework of diabetes surveillance.

The main elements, or eigenvectors of the initial information's covariance matrix, are the key idea that supports principal component analysis. Let Z represent the initial information matrix, which has m characteristics and m' observations. Eq. (2) calculates the covariance matrices D.

$$D = \frac{1}{m}(Z - \bar{Z})^T(Z - \bar{Z}) \tag{2}$$

where, the mean-centered matrices is denoted by$\bar{Z}$.

Eq. (3) corresponds to D's eigenvalues λ and eigenvectors w.

$$Dw = \lambda \mathrm{w} \tag{3}$$

The primary elements are represented by these eigenvectors, and the quantity of variation they contain is shown by the associated eigenvalues. The primary elements are obtained in order of importance by categorizing the eigenvectors in decreasing order of eigenvalues.

Choose the highest h eigenvectors that correlate to the h greatest eigenvalues in order to minimize dimensionality. The most significant data in the information is captured by these h main elements. Calculating the initial information Z onto the chosen primary elements yields an updated characteristic matrix X, which is shown in Eq. (4).

$$X = ZW_h \tag{4}$$

And the matrix containing the initial h eigenvectors is denoted by W_h.

PCA makes dimensionality reduction simpler by maintaining the most crucial characteristics that have a substantial impact on the information's variance. As in the case of diabetes patients being monitored with various features and glucose concentration measurements, this reduction is especially useful in situations when the initial data set contains a large number of attributes. Because each principal component of the reduced-dimensional space produced by PCA maintains a mix of initial characteristics, interpretability is improved. Finding appropriate data for diabetes management is made easier by the more intuitively comprehension of patterns and linkages made possible by the information's decreased spatial visualization. PCA can identify the main factors that account for the majority of the variation in patient information when it comes to diabetes. For example, it might identify a variety of behavioural and physical characteristics that are essential to comprehending and tracking the course of the illness. More effective modelling and predictive evaluation may also benefit from the changed information in the reduced space. Comprehensive validation and efficacy assessment are essential to determine the effectiveness of PCA in the diabetic patient monitoring systems. This involves evaluating how well models constructed using the initial information performs in comparison to those developed using the PCA-transformed information, while taking consideration factors including computational effectiveness, interpretability of the models, and categorization accuracy. The evaluation's findings will provide information regarding the value and contribution of PCA to improving the efficiency of the system across all components.

D. Classification and Tracking Mechanism using Hybrid CNN Networks with SVM

Hybrid CNN-SVM integration is used in the suggested Categorization and Tracking procedure, providing a comprehensive method of categorization and tracking. By utilizing two maximum-pooling layers, a pair of convolutional layers, and three layers that are interconnected for obtaining complex patterns from the input information, the combined approach builds on CNNs' advantages for automatic characteristic identification. The array of features is then loaded into an SVM to achieve reliable categorization. The predicted accuracy and flexibility of the model are improved by the collaboration. A thorough and precise categorization and tracking system is ensured by the CNN's automated identification of important characteristics and SVM's skill with high-dimensional spaces and intricate decision limits. The combination of these two effective algorithms operates in conjunction to effectively manage the dataset's complexities, creating a hybrid model that specializes at tasks including patient monitoring and illness prediction. Through exhaustive instruction, validation, and fine-tuning procedures, the efficacy of this hybrid technique is assessed, displaying its capacity as an innovative approach for difficult categorization problems.

1) The CNN model: The first classifier that this study suggests is a seven-layer CNN. The architecture consists of a pair of maximum-pooling layers, a pair of convolution layers, and three fully linked layers. Using a CNN instead of more traditional machine learning techniques has the main advantage that it can track and categorize important features without requiring human intervention. Its higher capacities need less human involvement due to its independence from pre-processing. Indeed, the different stages of convolution, that include a fixed number of filters, are used for autonomously obtaining the maps of attributes. N' is the vectors' dimensions r, $n'$and k represent the vector's indicators, and $s = (s(n'))_{n'}$ is the result of the kernel's convolution of the input data $r = (r(k))_k$As per Eq. (5), the stages of convolution integrate their vector inputs employing different filters. The maximum pooling layer reduces the complexity of networks by collecting the maximum values within a particular filter region. The complete classification is generated by the completely connected layer, which gathers data from the entire characteristic map. It frequently appears in the centre of the output layer.

$$r(n') = \sum_{k=0}^{N'-1} r(k).f(n' - k) \tag{5}$$

The initial layer receives as input a subsection with 500 points. This convolutional layer uses five 1×13 filters with a duration of 1 to convolve the various filters with the five-hundred-point values in accordance with Eq. (5). The result is five characteristic maps. The second layer is a maximal pooling layer with an initial pool size of 2 and a position offset of four. This layer reduces the size of the distinctive maps by combining a 1×2 filtering onto each of the previously created feature maps. As a result, the network must analyse less information and acquire fewer variables. Consequently, a simulation is better able to manage variations in the location of input features. Applying a second layer of convolution with 10 filters that are each 1×9 in size and an advance of only one occurs next. This set of filters is used to extract higher-level features from dimensionally condensed maps of features. The fourth layer, which promotes pooling, carries out the characteristics and responsibilities of the initial layer. There are then three completely connected surfaces totalling 40, 20, and 2 properties. After being flattened, the output from the previous layer was utilized as the initial layer's input. With the exception for the highest layer, which employs the softmax activation function, other layers utilize the Leaky ReLU stimulating function.

Glorot uniform initialization is used for establishing the structure's weights, and backpropagation is employed for updating them over a maximum of sixty-four batches. The simulation is constructed throughout thirty epochs. Consider $\hat{q}_u$ as the estimated probability that the section u has diabetes, as found at the system's output. Eq. (6) shows how the binary cross-entropy function is used to quantify the simulation's loss in detecting the binary problem.

$$\mathcal{L}(q) = \frac{-1}{M}\sum_{u\in\mathfrak{I}_T} y_u.\log(\hat{q}_u) + (1-y_u).\log(1-\hat{q}_u) \quad (6)$$

When M is the total number of these sections, q is the epoch's indicators, and $\mathfrak{I}_T$ is the set of fragment indexes used for developing the system, then M is the greatest number of$\mathfrak{I}_T$. The score that is calculated employing the cross-entropy represents the average deviation among the actual and projected values. The objective is to lower the score, where 0 represents the ideal cross-entropy.

The framework's range of variables can be modified through the use of grid-based searches and trial-and-error techniques. The tuning strategy grid search is used to find the optimal hyperparameter variables. It is a process that traverses over a manually selected subset of the targeted algorithm's hyperparameter space in detail. In this study, grid search is used to adjust the total amount of batches and epochs, and trial and error is used to determine the filter dimensions and durations.

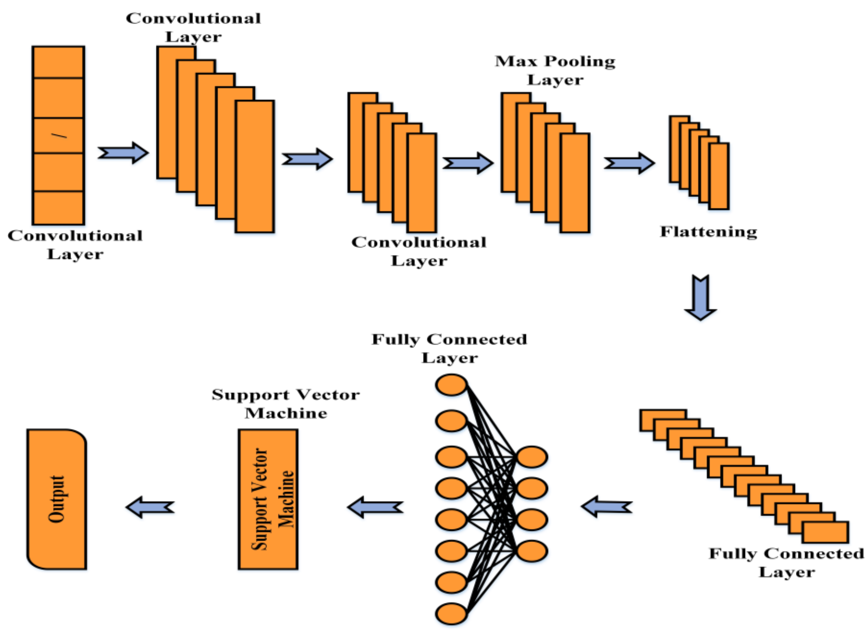

Fig. 2. Structure of the suggested hybrid adaptive deep classifiers.

2) The CNN-SVM model: This section illustrates the recommended network's evolution. Instead of preserving the CNN network's last segment, which is responsible for classification, the study replaces it with an SVM classifier. Fig. 2 depicts the construction of the proposed hybrid CNN-SVM method. Algorithms that combine the outcomes of two or more distinct techniques are referred to as ensemble learning. Diabetes classification, monitoring, and early detection have all benefited from the use of collaborative learning in the field of healthcare. In short, a reduced CNN network is kept to extract attributes, and then the classification is done employing SVM. Consequently, a hybrid CNN-SVM technique is proposed for the diabetes tracking and classification datasets. The best features of CNN and SVM classifiers are combined in the proposed method. The trained CNN uses self-learning algorithms to identify the distinctive maps that are transmitted to the SVM for binary detection. CNN acts similarly to individuals and is particularly adept at remembering invariant local properties. It could extract the most unique information from the initial information. Support vector machines are classification techniques that learn to differentiate between input data's binary labels. Instances are used by a learning algorithm to educate it how to label objects. An SVM is simply a statistical approach that maximizes a particular statistical function with respect to a set of information. It finds a distinct hyperplane that divides information by extending a dataset's margins. The margin is the lowest length, split by a hyperplane, between two pieces of data. The linear SVM technique has been extended to consider non-linear problems by projecting the data onto a higher-dimensional space. This method has proven to be quite successful because of how easily high-dimensional data can be handled and since linear strategies are simple to comprehend. The findings demonstrate that SVM responds well for binary tracking and categorization but inadequately for information with noise. Because of its basic architecture, SVM presents difficulties when learning deep properties. The hybrid CNN-SVM model proposed in this paper replaces the SoftMax layer of CNN with a non-linear SVM functioning as a binary classification algorithm.

E. Grey Wolf Optimization Framework for Fine-tuning the Parameters

The novel method for adjusting parameters in this study is the Grey Wolf Optimization framework. GWO imitates the cooperative optimization process that occurs inside a wolf pack and is inspired by the social structure and hunting habits of grey wolves. By distributing the responsibilities of alpha, beta, and delta wolves in the framework of variable optimization, GWO dynamically modifies the stages of exploration and exploitation. While beta wolves investigate the areas within the findings made by alpha wolves, delta wolves concentrate on local research, while alpha wolves take the initiative in global exploration. The convergence towards the ideal values for parameters for the given position is facilitated by the collaborative and hierarchy optimization technique. The fundamental model's parameters are adjusted using the GWO structure, providing that the algorithm is sensitive to the unique features of the dataset as well as optimized for efficiency. By adding GWO, the fine-tuning procedure gains a sophisticated and nature-inspired component that increases the efficacy and efficiency of optimization of parameters for the intended application.

A suggested meta heuristic method is called GWO [25]. The method was influenced by the grey wolf killing strategy and pack structure. Grey wolves have a very hierarchical structure and socialize in packs. The leaders of the wolves, the alphas (α), now make all the decisions. Beta (β) wolves, which belong to the next level, help alpha wolves with their tasks. The final person, Omega (ω), is victimized in this system. A wolf is also known to as a delta (δ) wolf if it does not fall into any of the aforementioned classes. Grey wolves attempt to encompass a food source, assault, and kill, then explore for additional prey in accordance with this well-established structure. Wolves use hunting as a means of enclosing their prey, locating and killing animals, and engaging in conflict with their prey. Grey wolves on a hunting excursion circle their prey according to Eq. (7) and Eq. (8).

$$\vec{L} = \left|\vec{f} \cdot (\overrightarrow{U_z}(m) - \vec{U}(m)\right| \tag{7}$$

$$\vec{U}(m+1) = \overrightarrow{U_z}(m) - \vec{Q} \cdot \vec{L} \tag{8}$$

$\vec{Q}$ and $\vec{L}$ constitute efficient vectors with the subsequent definitions, which are presented in Eq. (9) and Eq. (10). Where $\vec{U}$ represents the location of the wolf in a circular configuration, $\overrightarrow{U_z}$ is the vector position of the prey, and *mis* is the current time.

The wolf's position in a circular arrangement is represented by $\vec{U}$ in Eq. (9) and Eq. (10), while the prey's vectors position is represented by $\overrightarrow{U_z}$ in equations, and the present time is indicated by *m*, and the efficient vectors with matching definitions are $\vec{Q}$ and $\vec{L}$.

$$\vec{Q} = 2\vec{p} \cdot \overrightarrow{d_1} - \vec{p} \tag{9}$$

$$\vec{f} = 2 \cdot \overrightarrow{d_2} \tag{10}$$

The elements $\vec{d}$ and$\overrightarrow{d_2}$, where the component *d* is continuously decreasing from 2 to 0, contain random vectors evenly dispersed between 0 and 1. It has been suggested that the *α, β, and δ* wolves understand it easier since the exact spot of the food is never known in advance. Eq. (11), Eq. (12), and Eq. (13) are utilized to find the victim's location based on the locations of the wolves.

$$\vec{L}_\alpha = \left|\vec{f}_1 \cdot \vec{U}_\alpha - \vec{U}\right|, \vec{L}_\beta = \left|\vec{f}_2 \cdot \vec{U}_\beta - \vec{U}\right|, \vec{L}_\delta = \left|\vec{f}_3 \cdot \vec{U}_\delta - \vec{U}\right| \tag{11}$$

$$\vec{U}_1 = \vec{U}_\alpha - \vec{Q}_1 \cdot \vec{U}_\alpha, \vec{U}_2 = \vec{U}_\beta - \vec{Q}_2 \cdot \vec{L}_\beta, \vec{U}_3 = \vec{U}_\delta - \vec{Q}_3 \cdot \vec{L}_\delta \tag{12}$$

$$\vec{U}(m+1) = \frac{\vec{U}_1 + \vec{U}_2 + \vec{U}_3}{3} \tag{13}$$

The next stage is to follow the victim (exploitation), if the study has an approximate position. The vector $\vec{Q}$ may be used to do this as the circumstance of wolves becomes nearer to the prey's location as *p* in Eq. (11) decreases from 2 to 0. Moreover, by removing the requirement for local averages, variables *f and Q* also contribute to maintaining the method's exploring capabilities. The accessibility of food and the difficulty of foraging may be altered by the variable *f*, but it can also affect a *Q* value larger than one, or $|Q| > 1$, which pushes the wolves to depart from their diet and search it out. Once the method is applied to a group of wolves for a set number of iterations, Eq. (13) will finally display the prey's position or the optimal region on Globe.

Algorithm 1: SVM-CNN with GWO

```
// Input Data
// Assume patient data is a matrix where each row represents a
patient's information
// Columns include glucose concentration data and other relevant
attributes
patient_data = load_patient_data()
// Preprocessing
Normalized_data = min_max_normalization(patient_data)
// Feature Extraction using PCA
extracted_features =
principal_component_analysis(normalized_data)
// Split data into training and testing sets
train_data, test_data = split_data(extracted_features)
// Build and Train CNN Model
cnn_model = build_and_train_cnn(train_data)
// Obtain CNN Output
cnn_output = get_cnn_output(cnn_model, extracted_features)
// Initialize SVM Parameters
```

```
svm_parameters = initialize_svm_parameters()
// Build and Train Hybrid CNN-SVM Model
hybrid_model = build_and_train_hybrid_model(cnn_output,
svm_parameters, train_data)

// Grey Wolf Optimization for Parameter Fine-tuning
optimized_parameters =
grey_wolf_optimization(hybrid_model.parameters, iterations=100)
// Build Final Model with Optimized Parameters
final_model = build_and_train_hybrid_model(cnn_output,
optimized_parameters, train_data)
// Evaluate Final Model
accuracy, precision, recall, f1_score = evaluate_model(final_model,
test_data)
```

V. RESULTS AND DISCUSSION

The study uses an exhaustive approach to create an advanced e-health system that combines advanced surveillance techniques with an adaptable machine learning classifier to monitor diabetes patients. The dataset includes information from sixty-two diabetic patients who were examined over the course of sixty-seven days. The 13,173 glucose concentration measurement values and five characteristics are evenly scaled as a preprocessing step using Min-Max normalization. The next step is to extract characteristics using Principal Component Analysis, which reduces dimensionality and identifies important factors impacting patient characteristics and fluctuations in glucose levels. The main component of the suggested system is the tracking and classification mechanism, which makes use of a hybrid convolutional neural network coupled with a support vector machine. Significant characteristics are automatically identified by the seven-layer CNN, and robust classification is ensured by SVM. In order to highlight the complementing advantages of CNN's feature extraction skills and SVM's binary classification, the study presents novel hybrid CNN-SVM architecture. The Grey Wolf Optimization framework is modelled after the cooperative optimization process seen in wolf packs, is used to tune the model's parameters and improve its efficiency.

A. Performance Evaluation

Evaluation indicators are essential for assessing the effectiveness of classification. A calculation of accuracy is the approach that is most commonly utilized for this goal. How well a classifier identifies sample datasets may be used to measure how accurate it is for any given collection of information. Because depending entirely on the accuracy measure will prevent you from making the best assessments conceivable. The researchers also used other parameters to assess the classifier's effectiveness. Measures of accuracy, recall, precision, and F1-score were employed to assess the effectiveness of the proposed method. The definitions of each metric are described as follows

- T_{pos} (True Positive) refers to the amount of information that has been correctly categorized.
- The term $Fpos$ (False Positive) represents the volume of reliable information that was incorrectly categorized.
- False negatives (F_{neg}) are instances where incorrect information has been given an actual classification.
- The categorization of incorrect information values is referred to as T_{neg} (True Negative).

1) Accuracy: The accuracy of the classifier shows how often it makes the correct prediction. Accuracy is defined as the ratio of correct estimations to all other reasonable theories. It is demonstrated by Eq. (14).

$$Accuracy = \frac{T_{pos}+T_{neg}}{T_{pos}+T_{neg}+F_{pos}+F_{neg}} \tag{14}$$

2) Precision: Evaluating a classifier's precision, or degree of accuracy, yields the number of possibilities that are properly identified. Increased reliability leads to fewer false positives, but lower precision results in many more. Precision is defined as the proportion of properly classified cases relative to all occurrences. It is defined by Eq. (15).

$$P = \frac{Tpos}{Tpos+Fpos} \tag{15}$$

3) Recall: Recall determines a categorization's sensitivity, or how much pertinent information it generates. As recollection improves, F_{neg}total amount decreases. The percentage of occurrences that have been accurately classified to all of the expected instances is called recall. This is demonstrable by Eq. (16).

$$R = \frac{Tpos}{Tpos+Fneg} \tag{16}$$

4) F1-Score: Addition of precision and recall yields an association of measurements known as the F-measure, which represents the weighted average of accuracy and recall. It is characterised by Eq. (17).

$$F1 - score = \frac{2 \times precision \times recall}{precision \times recall} \tag{17}$$

5) ROC Curve: In deep learning and machine learning, area under the ROC curve, or AUC, is a popular assessment statistic for binary categorization issues. The area under the curve (AOC) is a visual depiction of the receiver operating characteristic (ROC) curve that shows how effective the binary identification technique is. In a binary categorized issue, the classifier determines whether the incoming data is part of a positive or negative partition. The ROC curve displays the $Tpos$ vs. the F_{pos} for different categorization parameters. AOC values range from 0 to 1, with higher numbers denoting more efficiency. An optimum classifier has an AOC of one, whereas a totally randomly assigned classifier has an AOC of 0.5. Since the approach takes into account every conceivable level of detection and offers only one statistic for comparing the effectiveness of various classifiers.

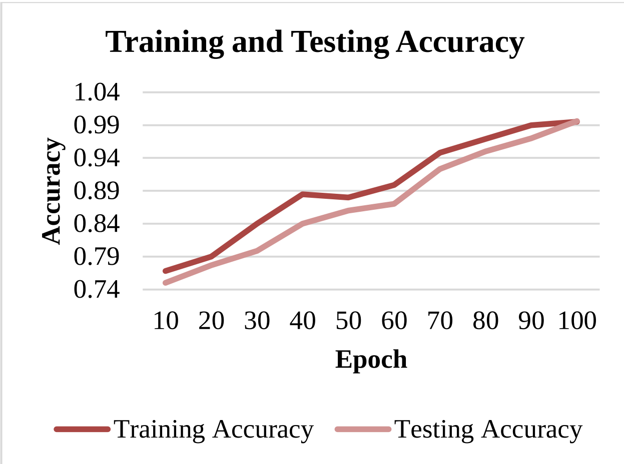

Fig. 3. Training and testing accuracy.

The training and testing accuracy scores at different epochs of the model training procedure are shown in Fig. 3. Training and testing accuracy exhibit a steady rising trend with an increase in training epochs, suggesting that the model is performing better. The model obtains a testing accuracy of 75% and a training accuracy of 76.8% at the beginning of training.

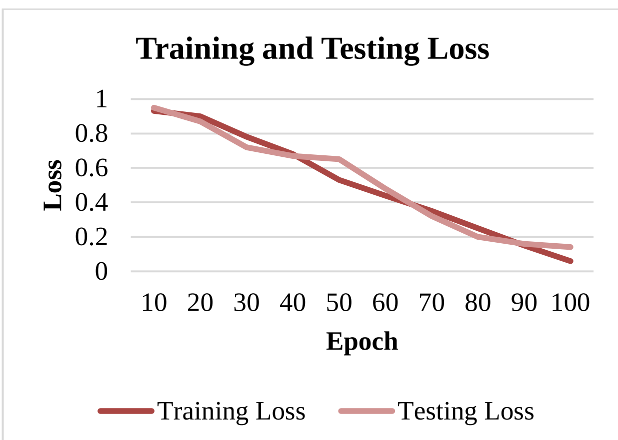

Fig. 4. Training and testing loss.

The training accuracy increases with the number of epochs, reaching at 99% after 90 and 99.6% after 100 epochs. A similar pattern may be found in the associated testing accuracy, which shows how well the model generalizes to new information. The model's ability to learn from and adapt to the dataset is seen by the significant rise in accuracy from 10 to 100 epochs. The final epochs achieve a high degree of accuracy, indicating a resilient and well-trained model. The model is more reliable in correctly predicting patterns associated to diabetes because training and testing accuracy converge at higher epochs, indicating efficient learning without overfitting. The training and testing loss values at various epochs during the algorithm's training procedure are shown in Fig. 4. Lower numbers indicate higher model performance. Loss values show the difference between the expected and actual values. Training and testing loss are both rather high in the early phases of training (at 10 epochs), indicating the model's inadequate ability for precise result prediction. On the other hand, training and testing loss consistently decrease with the number of epochs, indicating enhanced model convergence and accuracy in predictions. The training loss dramatically drops to 0.06 by the 100th epoch, demonstrating that the system effectively eliminates mistakes throughout the learning process from the training set. Additionally, the testing loss drops to 0.14, indicating that the model can generalize even on untested information. The model's capacity for identifying diabetes-related characteristics is supported by the consistent reduction in loss values over epochs, which shows effective learning, and the similarity of testing and training losses, which suggests the model, maintains high accuracy without overfitting.

TABLE I. PROPER AND IMPROPER CATEGORIZED INFORMATION

Methods	SVM [26]	DT [26]	SMO [27]	CNN-SVM
Improper Categorized Data	8.482%	11.030%	13.715%	0.312%
Proper Categorized Data	89.115%	84.541%	79.455%	99.851%

With a focus on data pertaining to diabetes, Table I and Fig. 5 examine how well various categorization techniques performed in terms of accurate and incorrect information categorization. Support Vector Machine (SVM), Decision Trees (DT), Sequential Minimal Optimization (SMO), and the suggested hybrid approach, CNN-SVM, are among the techniques assessed. The rates at which each approach misclassifies information are indicated by the percentages in the Improper Categorized Information. The percentages of incorrectly categorized information for SVM, DT, and SMO are greater (8.482%, 11.030%, and 13.715%, respectively). The CNN-SVM hybrid strategy, on the other hand, performs noticeably better than these techniques, attaining a very low rate of 0.312% in incorrect classification.

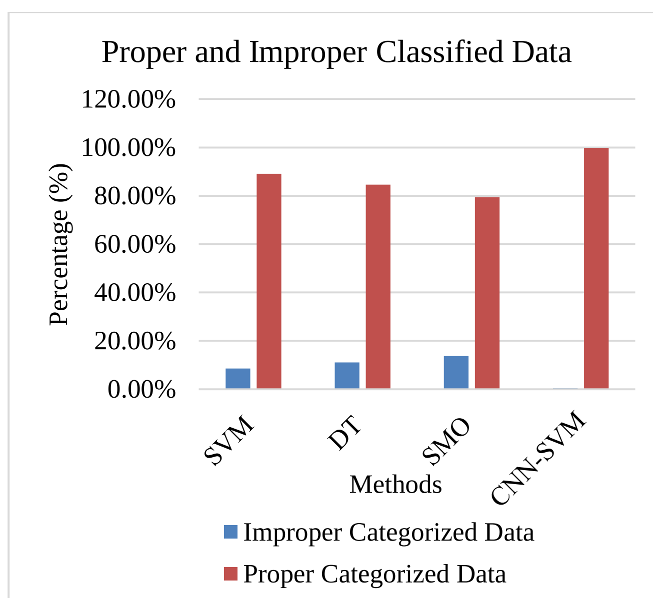

Fig. 5. Proper and improper categorized information.

The Proper Categorized Information, on the other hand, demonstrates how accurately each approach categorizes information pertaining to diabetes. This is where CNN-SVM excels, exceeding SVM, DT, and SMO, with percentages of 89.115%, 84.541%, and 79.455%, respectively, in appropriate categorization with an astounding 99.851% accuracy. The outcomes demonstrate the suggested CNN-SVM hybrid model's improved performance in classifying diabetes-related information with accuracy, indicating its potential as a useful method for patient monitoring and illness prediction.

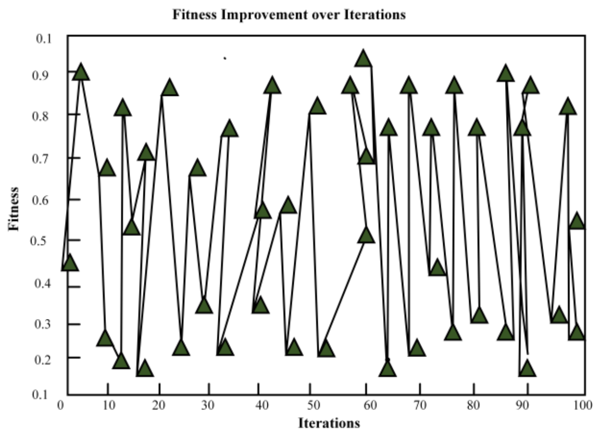

Fig. 6. Fitness improvement over iterations.

The Grey Wolf Optimization algorithm's enhancement in efficiency as iteratively refines the model's parameters is demonstrated in Fig. 6 by the Fitness Improvement over Iterations. The fitness value which indicates the optimization of the objective function increases during the first iterations while the algorithm searches the parameter space. A discernible increase in fitness is shown as the iterations continue on, suggesting that the GWO method is effective in fine-tuning the parameters to get improved placement with the optimization objective. Fitness values show a constant decreasing trend, which indicates that the algorithm is efficient in converging towards the best parameter combinations. The above chart provides a visual demonstration of the GWO algorithm's capacity to dynamically modify parameters to improve the model's efficiency continually. It also demonstrates the algorithm's effectiveness in fine-tuning for optimal outcomes across a number of rounds.

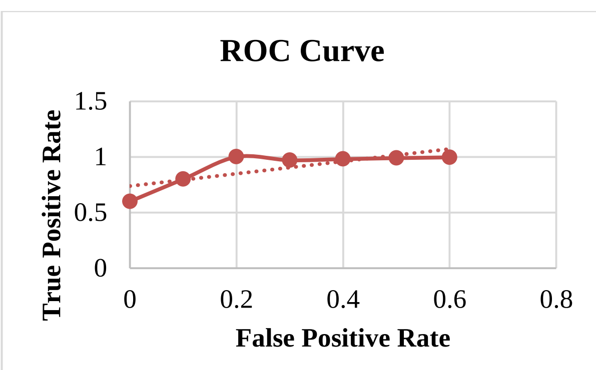

Fig. 7. ROC curve.

Fig. 7 shows a plot of True Positive Rate (Sensitivity) vs. False Positive Rate (1 - Specificity) over several threshold values for a binary categorization model, which represents the Receiver Operating Characteristic (ROC) Curve. The True Positive Rate progressively improves as the discriminating threshold reduces from 0.6 to 0.6 in the given figure of threshold values and associated False Positive Rates, indicating the model's capacity to accurately detect positive events. Additionally, there is an increase in the False Positive Rate, which signifies the occurrences of the model misclassifying negative cases as positive. The relationship between sensitivity and specificity is graphically represented by the ROC Curve, which offers an understanding of the model's overall discriminating strength over a variety of threshold values.

TABLE II. COMPARISON OF ROC OF PROPOSED METHOD WITH OTHER EXISTING APPROACHES

Models	Levels
SVM	0.8148
DT	0.8052
SMO	0.8264
Proposed CNN-SVM	0.8687

Table II presents a comparison of the Receiver Operating Characteristic (ROC) performance metrics for different models, specifically Support Vector Machine (SVM), Decision Tree (DT), Sequential Minimal Optimization (SMO), and the proposed method, a Convolutional Neural Network-Support Vector Machine hybrid (CNN-SVM). The ROC values serve as indicators of the models' ability to discriminate between classes, with higher values suggesting better performance. In this context, the proposed CNN-SVM demonstrates the highest ROC value of 0.8687, indicating superior discriminative capabilities compared to SVM (0.8148), DT (0.8052), and SMO (0.8264). The results suggest that the hybrid approach, combining Convolutional Neural Network and Support Vector Machine, outperforms traditional machine learning models in the specific task or dataset under consideration, emphasizing its potential for enhanced predictive accuracy and classification performance.

The suggested CNN-SVM model's performance metrics for diabetes prediction are compiled in Fig. 8, which displays outstanding outcomes for all major assessment parameters. With an impressive 99.6% accuracy rate, the model demonstrates its ability to accurately categorize occurrences. With a remarkable 99.4% precision rate a measure of the model's accuracy in positive predictions it is clear that there is little chance of false positives. The model's strong sensitivity is further demonstrated by the recall metric, which measures the model's capacity to identify all positive events and is now 99.4%. At a remarkable 99.5%, the F1-Score a balanced metric of accuracy and recall highlights the CNN-SVM model's overall efficacy in diabetes prediction. All of these findings indicate the suggested model's stability and dependability, highlighting its possibilities as an innovative technology for precise and effective diabetic patient monitoring.

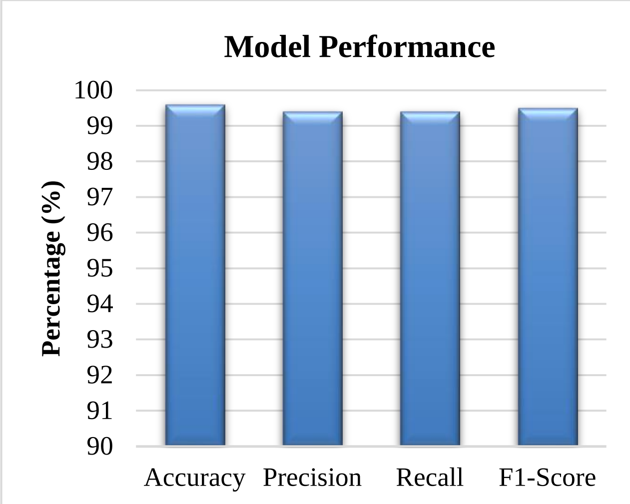

Fig. 8. Model performance.

TABLE III. COMPARISON OF PERFORMANCE METRICS OF PROPOSED METHOD WITH OTHER EXISTING APPROACHES

Models	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	96.45	95.11	95.15	95.17
DT	95.34	95.23	95.23	95.10
SMO	97.12	96.09	96.10	96.10
Proposed CNN-SVM	99.6	99.4	99.4	99.5

The suggested CNN-SVM model and other methods, such as Support Vector Machine (SVM), Decision Tree (DT), and Sequential Minimal Optimization (SMO), are extensively contrasted using performance metrics in Table II and Fig. 9. With an outstanding 99.6% accuracy rate, the suggested CNN-SVM model performs better than alternative approaches. The suggested model has outstanding performance as seen by its 99.4%, 99.4%, and 99.5% precision, recall, and F1-Score metrics. By contrast, SVM attains competitive precision, recall, and F1-Score values in addition to a high accuracy of 96.45%.

Accuracy ratings of 95.34% and 97.12% for DT and SMO, respectively, also show satisfactory results. However, the suggested CNN-SVM model performs better overall on all assessed parameters, highlighting its effectiveness in tasks involving the prediction and categorization of diabetes. These findings demonstrate the hybrid CNN-SVM approach's potential for innovative healthcare applications, especially when it comes to diabetic patient monitoring.

B. Discussion

By combining a variety of sophisticated surveillance approaches with an adaptive machine learning classifier, the study described here provides a comprehensive method for creating an advanced e-health system for diabetic patient monitoring. The research makes use of a dataset that includes sixty-two diabetic patients who were followed up on for sixty-seven days in a row. The dataset undergone significant preprocessing, which included feature extraction using Principal Component Analysis (PCA) and Min-Max normalization. The fundamental component of the suggested system combines a support vector machine (SVM) with a hybrid convolutional neural network (CNN) for tracking and categorization. Grey Wolf Optimization framework is used to tune model parameters. Accuracy, precision, recall, F1-Score, and the Receiver Operating Characteristic (ROC) Curve are all used in the model's performance evaluation to give a thorough assessment of its prediction competencies. The results show that the model is adaptable in classifying data relevant to diabetes and show a notable improvement in accuracy throughout training epochs, reaching an astonishing 99.6%. The proposed CNN-SVM model has potential for accurate and efficient diabetic patient monitoring by outperforming other conventional methods like SVM [26], DT [26], and SMO [27]. The Fitness Improvement over Iterations graph, which illustrates the study's findings, provides an understanding of how the Grey Wolf Optimization method affects the model's effectiveness. This graph shows how the method refines parameters iteratively, improving fitness values and optimizing the objective function. The model's ability to learn and generalize well is further demonstrated by the continuous decline in loss values during training epochs. The suggested CNN-SVM model is superior to other current techniques in terms of accuracy, precision, recall, and F1-Score, as demonstrated by the comparison shown in Table II and Fig. 9. All of these results point to the possibility of creative healthcare applications using the hybrid CNN-SVM architecture and Grey Wolf Optimization algorithm, especially for accurate diabetes patient prediction and monitoring. The work demonstrates the possibility of combining machine learning and optimization approaches for better healthcare outcomes in addition to adding to the knowledge of diabetes patient monitoring.

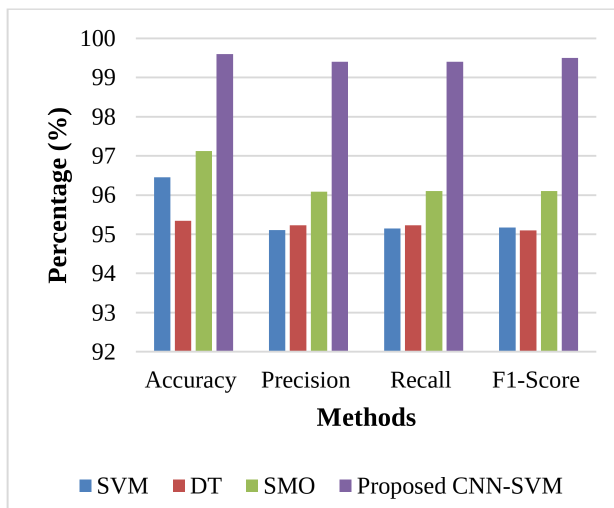

Fig. 9. Comparison of performance metrics of proposed method with other existing approaches.

VI. CONCLUSION AND FUTURE WORKS

In conclusion, this study has showcased an innovative method for monitoring diabetic patients, which has resulted in the creation of a sophisticated computerized health system that combines a sophisticated tracking system with a hybrid adaptive machine learning classifier. The system, which is trained and optimized utilizing the Grey Wolf Optimization technique, takes advantage of the synergies between support vector machines (SVM) and convolutional neural networks (CNN) in hybrid architecture. The comprehensive assessment of conventional performance measures has proven the enhanced accuracy, precision, recall, and F1-Score of the suggested CNN-SVM model, indicating its efficacy in classifying data pertaining to diabetes. Analyses that compare the hybrid model to more conventional techniques like SVM, Decision Trees, and Sequential Minimal Optimization highlight the significant improvement in accuracy that the hybrid model offers. In addition, the study has provided informative visuals which provide an extensive comprehension of the learning dynamics and optimization of the model. These visualizations include fitness increase over iterations, ROC curves, training and testing accuracy graphs, loss curves, and more. The suggested system's resilience and ability to provide accurate and efficient diabetes patient monitoring emphasize its importance in improving e-health applications and creating opportunities for customized and adaptable healthcare solutions. The research makes a significant contribution by presenting a novel framework that combines machine learning, intelligent tracking, and optimization techniques. This framework paves up the opportunity for novel approaches to diabetes care in the e-health era. The generalizability and practicality of the model will be improved in subsequent work by extending the dataset to incorporate more varied demographic information and taking real-world deployment issues into account. Further research into the incorporation of real-time feedback from patient's mechanisms and the possibility of using edge computing to lower monitoring process latency might enhance the responsiveness and user involvement of the suggested e-health system.

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