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IoT based Smart Healthcare System in Cloud Environment

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ABSTRACT

People are increasingly concerned about their health and need to keep it properly. The rapidly growing human population needs sophisticated systems to forecast patients' health status and appropriate treatment. The newest technological breakthroughs and innovations assist the healthcare business overcome prediction challenges. The Internet of Things (IoT) and Deep Learning technologies help transport health-related data from the local entity to the server and preserve it after evaluation. These regulations allow the medical sector to develop new health prediction technologies while saving countless lives. Parallel to this, these characteristics attract various hackers or invaders to get health data and abuse it. So, the main worry of internet-based health record monitoring and analysis is security. This research introduces a new deep learning technique called Learning Assisted Secured Health Prediction (LASHP), developed from the traditional learning model called Artificial Neural Network (ANN). This technique combines Deep Learning, Cryptographic Security Mechanisms, and the Internet of Things to create a durable model. IoT logic transports data securely from local units to remote servers for processing. The suggested healthcare prediction method is secured using the Modified Cipher Scheme (MCS), linked with the proposed LASHP logic. Thus, the suggested Learning Assisted Secured Health Prediction technique is efficient and effective in the next portion of this work.

KEYWORDS

ANN; Deep Learning; Health Care; Internet of Things; IoT; LASHP; Modified Cipher Scheme; Secured Health Prediction

1. INTRODUCTION

As the senior population grows, retirement and healthcare will experience substantial strain. Healthcare insurance for older adults is a considerable impediment to allocating scarce health assistance. The Internet of Things (IoT) seems to be a potential solution for reducing healthcare demand. Healthcare systems in the industry have advanced significantly due to the fast expansion of wireless communication networks, including multispectral telecommunication, Wi Fi-enabled data services, and other communication pathways. This paper presents a real-time Big Data-assisted healthcare assessment methodology concerning the mix of deep learning network models called Artificial Neural Networks (ANN). The system comprises two components: a deep learning-enabled network model for detecting abnormalities in the cloud environment and an Artificial Neural Network model for diagnosing cloud conditions. The system can completely exploit the cloud structure's fundamental essence. Still, it can also fully use its tremendous processing capacity by alleviating the vital signs such as electrocardiograms, electromyograms, temperature, hypertension, and blood sugar levels might be detected using Big Data analytics-based healthcare systems. By setting anomalies, it is possible to foresee the potential of sickness, minimize the effort of medical personnel, and relieve some of the strain on the health care service. Health care services associated with Big Data processing demand massive volumes of data to be gathered via the Internet of Things assisted sensors, analyzed, and decisions must be made on the cloud computing layer.

Consequently, genuine data transfer from Internet-assisted embedded sensors continues to be a significant difficulty. When an Internet of Things device connects remotely by creating relevant signals, it uses considerable power. For instance, in-body implantation, like a cordless capsule used in gastrointestinal inspections, uses double the effort consumed to transmit the information as the sensor detects an image [7]. And from the other extreme, low battery technology limits the product's efficient management period. Furthermore, raising the storage capacity of the shell produces a lot of the capsule region, which indeed creates difficulties in digesting [8]. The gadget's dimensions and storage capacity will undoubtedly play a significant role in the broad appeal of in-body implantation and internal sensors. As a result, novel technologies for legitimate information transfer from in-body devices and internal body sensors have emerged as critical research paths for medical system advancement. Multispectral communication is a new passive communications channel that can significantly improve sensor internet connectivity and power efficiency. It is predicted to become a viable transmitting data option for low-power Internet of Things supportive applications [9]. Multispectral communication offers applications in low-power contexts such as embedded applications, economical Internet of Things, linked homes, and wearable technology. It successfully solves the perception issue between devices. Indeed, the economic benefits of multispectral communications will significantly impact how physicians and patients communicate and how patient information is conveyed throughout healthcare systems [10].

This paper provides a real-time Big Data-assisted healthcare assessment system concerning ambient multispectral telecommunication. This method consists of a real-time extensive data analytics system powered by Artificial Intelligence and an information transmission system powered by contextual multispectral networking.

The practical Big Data-assisted health assessment model is at the heart of tracking and evaluating patients' health. In contrast, the wireless data model assumes that the genuine large-scale data healthcare examination has strong data communication assurance. The authentic Big Data-assisted healthcare assessment system monitors and diagnoses the user's health condition using a combination of deep and Artificial virtualized element's computational load. The healthcare system will experience great strain as the aging population [1]. The primary health hazards to older adults are chronic illnesses such as hypertension, heart problems, strokes, diabetes, malignancy, and respiratory ailments [2]. As the aging population grows, the prevalence of chronic illnesses will undoubtedly increase, posing a significant problem for allocating scarce medical resources. The Internet of Things (IoT) is commonly touted as a way to relieve pressure on healthcare systems.[3]. Healthcare systems associated with Big Data processing have advanced significantly with the emergence of fog-assisted cloud computing [4][5], Artificial-Intelligence (AI) [6], and the IoT. Anomalies in Neural Networks. The system consists of data collecting, cloud processing, and dataset handling. Sensors are responsible for accumulating data from the hospital/patient end. The Internet of Things is reliable for data-oriented communications, and the health data model comprises the data processing layer. Based on these kinds of data, it is transferred to the cloud layer using a variety of various wireless data channels.

The cloud computing layer employs deep neural networks to identify anomalies depending on specified tasks. Finally, the cloud infrastructure executes Artificial Neural Network-based learning on the anomaly report and the Meta information transmitted by the cloud environment. It provides the primary explanations for the phenomenon and the associated health emergency response plans. The inclusion of the cloud environment significantly lowered the overall health monitoring structure's computational load, and the IoT supports data communication load reduction over the network infrastructure.

1.1 Cipher Policy Assistance

The proposed approach concentrates on security issues presented in the existing healthcare system. For considering the security enhancement in the proposed method, the logic of the Novel Hybrid Encryption Mode (NHEM) scheme is reviewed [11], and derived new security-assisted cipher model called Modified Cipher Scheme (MCS). This scheme handles the data acquired from the patients based on the secret key generated randomly while processing the data. The private key is generated based on three metrics: data processing period, length of data going to process, and the random key.

Based on these factors, the secret key is generated. Nobody can guess or hack it due to their convenience. The proposed approach, called Modified Cipher Scheme, is robust and reliable in straightforwardly securing health-related data. The following figure, Figure 1, illustrates the perception of a proposed crypto model called MCS in detail with proper specifications. This cryptographic model processes the health information according to a 512-bit processing sequence. Therefore, it is more secure than other conventional approaches presented in the literature.

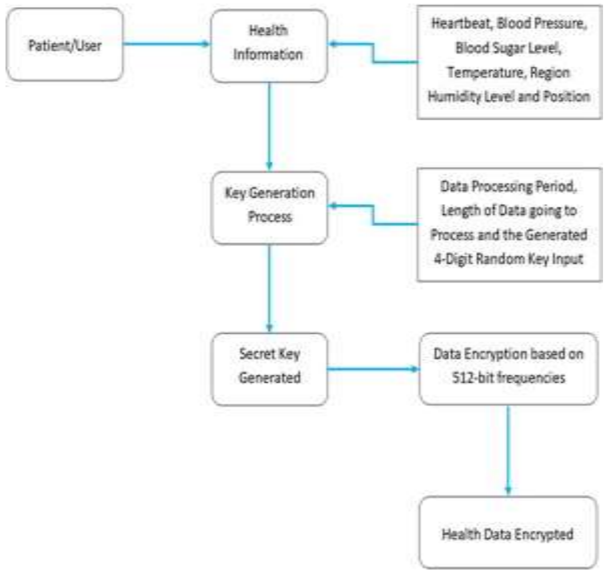

Fig. 1 Modified Cipher Scheme Process Model

2. RELATED WORK

The world increasingly relies on Internet of Things (IoT) technology to monitor and operate objects remotely and more precisely. The Internet of Things (IoT) may be precious in the medical and healthcare areas since it enables remote monitoring of chronic illnesses, vital sign monitoring, emergency detection, diagnosis, and prediction of patient conditions or disorders. IoT is beneficial in the case of senior health care and monitoring, which are frequently chores that need the complete attention of a caregiver or medical professionals. This survey highlights the importance and categorization of IoT-assisted solutions for senior health care. In addition, the paper reviews research papers on the development and use of IoT-assisted healthcare systems for the elderly.

Additionally, the article [12] discusses the essential architecture of IoT-based healthcare systems and their application, including wearable, in hospitals and at home. Finally, the paper discusses the security risks inherent in adopting IoT processes that support remote access to sensitive information and data preservation. According to the researched documents, the Internet of Things will continue to grow in popularity as a technology trend that enables the creation of affordable, dependable, and secure senior health care and assessment processes.

The Internet of Things has undeniably changed the healthcare business, and it benefits physicians, patients, households, healthcare facilities, and even insurance firms. The Internet of Things (IoT) may readily improve patient care processes by utilizing healthcare mobility services, upcoming health services, and other analogous technologies. It can help the healthcare business offer efficiency by enabling machine-to-machine connectivity, interoperability, data transfer, and knowledge sharing [13].

Furthermore, technology-driven solutions can save expenses by eliminating needless trips, leveraging higher-quality resources, and optimizing the appearance and allocation. Imagine if something could alert physicians when a patient's vital signs go crazy or if a person isn't maintaining adequate care for his health. Might that data be given to physicians on the task. IoT might help keep client information in the cloud and minimize the entering of information into Emr systems. IoT additionally guarantees that every minuscule amount of data is taken into account before ensuring efficient judgments for patients. Additionally, this could be utilized as a household monitoring tool and a tool for maintaining healthcare compliance. This is how the Internet of Things changes people's lives [14].

Real-time surveillance using mobile apps could save innumerable lives in medical emergencies, including cardiac arrest, respiratory problems, and diabetes [15]. IoT systems may acquire all health-related data and move the machine over the information connection through real-time monitoring via a

digital medical system coupled with a smartphone application [16].

Similarly, as the switch, the IoT app may collect body temperature, insulin levels, oxygen, body weight, and even ECGs. Records will be maintained on the cloud and maybe quickly shared with those who need them, like physicians or other outside experts, [17] that may help them comprehend the situation more clearly and quickly. IoT devices have made a significant contribution to the healthcare industry. Proactive identification of vitals and rapid response might spark a modern healthcare dramatic transformation. [18] Several personal health monitoring systems (PMS) are on the market, such as glucometers, wrist monitors, digitized thermometers, electronic pressure devices, etc. Our goal is to connect many PMS devices from various sensors to an IoT microcontroller and collect data while processing and manipulating the data in a cloud-based system [19].

With the Internet of Things automating different aspects of health care, technology has changed the profession of medicine. This project aims to develop a wireless system that provides real-time monitoring of patients' health care, emphasizing Intra-Venous fluid dynamic regulations and oversight. Additionally, the device captures the patient's heartbeats and continuously checks the body's temperature. Traditionally, physicians must be physically available to check a patient's status and suspend the Intra-Venous infusions to stop blood leakage into the Intra-Venous tubing. The current system is meant to stop the Intra-Venous drip as soon as it's done and notify the doctor and nurse's aide by using an app containing important patient information, eliminating the requirement for continuous human interference for these functions and hence removing the possibility of crises. This project will design and construct a computer system infrastructure based on ontologies. Additionally, this will be able to track the patient's health status remotely and securely with minimal human resources [20].

Internet of Things-based e-health care systems is frequently used for remote health screening and treatment to lower health care costs. Patient data is kept in a health cloud and is accessible to medical practitioners at any time. As a result, secure data transmission is critical for treatment and monitoring purposes. Additionally, when maintaining the patient's information, it must be protected against abuse and manipulation of data due to the ease with which other devices may track it. Due to the limited capabilities of IoT devices, it is challenging to encrypt data using advanced cryptographic algorithms. For this reason, lightweight cryptographic algorithms are appropriate. We propose a novel block cipher approach in this study for the safe transmission of information from all these connected devices [21].

In today's society, many difficulties in health and medicine result from the absence of prescribed medications and supervision at the appropriate time. Several digital innovations and Internet of Things-enabled gadgets enable remote monitoring of a patient's condition. Specialists in India use such intelligent devices and technologies to check the patient's health status. This article [22] introduces a kit that is premised on these technology systems and is capable of measuring a patient's diverse physical parameters such as heart rate, temperature, respiration, and vital signs as well as recording the brain waves, muscle, modifications in sympathetic stimulation task and oxygen-carrying particles in the plasma. The evaluation results are then conveyed via an internet connection.

This paper proposes a wireless wearable module for IoT-based remote patient monitoring. Physicians can use this module to keep track of their patient's heart rates, oxygen saturation levels, and core temperature. The Node-MCU device, a controller, and a WiFi chipset are all used in this module. In addition, a renewable power extractor is designed as a source of electricity to extend the module's lifespan. This extractor comprises flexible rubber photoelectric arrays, a recharging microcontroller, and a rechargeable battery. The extractor is tested in full sunlight and partially overcast weather. During a cycle of operation, the Internet-of-Things-based wearable sensor module uses an average of 20.23 mW. It has a lifespan of 28 hours in live mode. Furthermore, testing results indicate that the module's recorded vital information is safe on a Ubidots remote server [23].

3. METHODS AND ALGORITHMS

This paper introduced a new deep learning model called Learning Assisted Secured Health Prediction (LASHP) with enhanced security features associated with integrating a cipher algorithm called Modified Cipher Scheme (MCS). These two logics are combined and provide complete healthcare prediction services with the help of the latest technologies. Furthermore, the logic of Artificial Intelligence is included in this approach to predict the disease based on the dataset acquired by using the real-time patient data collected based on sensors associated with the Internet of Things module. This paper uses a novel WiFi-assisted internet service-enabled NodeMCU controller to acquire health information from sensor units and associate it with the respective Comma-Separator-Value (CSV) file to train the model. Once the model is created, the data is loaded into the execution entity to test it with real-time patient records. The dataset loaded from the IoT remote server consists of several helpful pieces of information regarding the patient health metrics, which is clearly illustrated in the following figure, Fig.2. It portrays the exact parameters taken into consideration for processing the health records and attaining the proper prediction scenario.

```
Int64Index: 296 entries, 0 to 302
Data columns (total 14 columns):
 #   Column
---  ------
 0   age
 1   sex
 2   chest_pain_type
 3   resting_blood_pressure
 4   serum_cholestoral
 5   fasting_blood_sugar>120
 6   electrocardiographic_results
 7   max_heart_rate
 8   excercise_induced_angina
 9   st_depression_after_resting
 10  excercise_st_segment_slope
 11  flouroscopy_colored_vessels
 12  defect_type
 13  has_heart_disease
dtypes: float64(1), int64(13)
memory usage: 34.7 KB
```

Fig.1 Dataset Model Loaded from the IoT Cloud Server

The proposed approach manipulates the features of the loaded model concerning the methodology called 'Sequential-Feature-Selector (SFS)', in which this model is used to add the features to generate a subset in a greedy model as well as it can subtract the features to generate a subset in a greedy model. This predictor determines the optimal features to include or drop in every phase depending on the estimator's cross-validation performance. Even If nothing is specified, just 50% of the available attributes are picked. A different search technique called the Sequential-Feature-Selection method is used to minimize an original 'd' dimension-based feature set to a 'k' dimension-oriented feature set where k<d. The purpose of feature selection techniques is to dynamically pick a set of the most pertinent attributes to the task. The purpose of feature extraction is dual: By deleting extraneous features or noise from the model, we may increase its computing performance and minimize its prediction error. In summary, the purpose of the section is to delete or add new features (one at a time) dependent on the effectiveness of the respective classification model until the target feature set of size 'k' is obtained. The SFS supports four distinct kinds of Sequential-Feature-Attributes (SFA):

(a) Sequential-Forward-Selection (SFS)
(b) Sequential-Backward-Selection (SBS)
(c) Sequential-Forward-Floating-Selection (SFFS)
(d) Sequential-Backward-Floating-Selection (SBFS)

Sequential-Forward-Floating-Selection and Sequential-Backward-Floating-Selection can be thought of as expansions of the basic Sequential-Forward-Selection and Sequential-Backward-Selection algorithms. The floating methods contain extended durations of rejection or addition to delete attributes that have been incorporated (or removed), allowing for sampling a more remarkable set of feature subgroup possibilities. That is critical to highlight that this phase is conditional and occurs only if the obtained feature subgroup is deemed "superior" by the criteria algorithm after a specific characteristic is removed (or added). Additionally, an extra check allows the process to bypass the contingent isolation phases if it becomes stuck in loops. The following algorithm, Algorithm-1, illustrates the logic of the proposed Sequential-Feature-Selection in detail with proper specifications[24-26].

Algorithm-1: Sequential-Feature-Selector

Input $Y = \{y_1, y_2, y_{3,.............}, y_d\}$

The Sequential-Feature-Selector logic acquires the completed dimension-based features as a source.

Output $X \leftarrow \{x_j \mid j = 1,2,3, \ldots, k,\ x_j \in Y\}$, Where $k = 0,1,2,3, , d$

The Sequential-Feature-Selector logic includes a subset of features with the selected set k. The k<d specifies the selected priority.

Initialization- Phase: $X_0 \leftarrow \emptyset, k \leftarrow 0$

We begin an approach with just an arbitrary function $\emptyset$, which signifies 0 in the k set.

Inclusion:
1. $X_k \leftarrow argmax(J).\{X_k + x\}$, where $x \in Y - X_k$
2. $X_{k+1} \leftarrow X_k + x^{+}$
3. $k \leftarrow k + 1$
4. Go to Step-1

In this step, excess features are added, x^{+} to our part set X_k

x^{+} defines the feature-maximized state. Therefore, if it is concatenated with X_k, it is associated with the best classification performance.

Repeat the same process until the inclusion procedure is done.

Removal:
1. $x \leftarrow p$

Feature subset-based X_k features are associated with the actual subgroup concerning the length of k. It consists of desired features 'p' that refers to the priority.

The logic of Learning Assisted Secured Health Prediction (LASHP) is presented to categorize health-related information into favorable and unfavorable classifications. The classification performance indicates that the information's result has been appropriately obtained; the values are denoted by 1 and 0. '1' represents a favorable outcome, whereas '0' means unfavorable. The unfavorable class indicates that the data output is incorrect; if this is the case, the operation is repeated until the correct information is retrieved. Fundamentally, the output weights of Artificial Neural Network (ANN) architecture are assigned randomly at the start of the learning process. This article focus on avoiding arbitrary initiation of parameters on LASHP because inappropriate beginning contributes to a prolonged intermediate network and proposes the suggested method of optimizing weights using the recommended optimization technique. The improved weights are then used in the classifier to ensure accurate classification. The details of presented algorithm is available in details in [27-31].

Traditionally, machine learning relies on shallow nets composed of one information and one output layer, with nearly one hidden layer in between. The suggested categorization model operates similarly to existing defined neural network logics. It generates neurons with learnable weights and biases. The LASHP algorithm is fed the feature set $C_n = C_1, C_2, C_3, C_4$, and it provides the optimum weights for each layer. In this case, the LASHP technique uses improved weights to produce more accurate classification results. The LASHP classifier is typically composed of three layers: a pooling layer, a convolutional layer, and a fully connected layer. The ANN model's final output choice is based on its weights and clusters, which are updated according to the following equation:

$$Q_n \leftarrow \Sigma_{n_{1}j=1} C_{n^*} W(d) \qquad (1)$$

Where Q_n indicates the volume of the input data layers, Cn represents the health information set, and W(d) defines the health information weight. Data optimization was performed using each document's health data weight value. The weight ratio is derived by multiplying the data value of the Closed-Item-set by the output parameter. The volatility value was determined using the health data's unique number of words. Thus, in this case, the aggregation measure is the weight ratio. The suggested optimization strategy significantly improves the accuracy and resilience of the learning process, and the optimization nature is used to optimize the weight in each layer of LASHP.

Algorithm-2: Learning Assisted Secured Health Prediction

Step-1: Determine the weight of an arbitrarily significant population of n host nests (W(d) = 1, 2, 3,...n).

Step-2: Acquire a cuckoo using the Levy flight behavior equation, which is defined as:

$$Z_i(t+1) \leftarrow Z_i(t) + \text{a} + L(\lambda), \Omega > 0 \qquad (2)$$

$$L(\lambda) \leftarrow t(-\lambda), 1 < \lambda < 3 \qquad (3)$$

Step-3: Determine its fitness function F_i is the difference between the two solutions. The new solution is substituted with the randomly chosen nest.

Step-4: Determine the F_i threshold value (T_h) and divide the data into low priority (L_P) and high priority (H_P) categories based on the threshold value. The T_h value that is considered in this procedure is as follows:

$$T_h \leftarrow (H(1-\Omega))/T \qquad (4)$$

Where T_h denotes the threshold value, H is the average weight, and T represents the total weight.

Step-5: Among the host nests j, choose an H_P nest and compute its fitness F_j.

Step-6: If $F_i < F_j$, replace j with a new solution or let j be the solution.

Step-7: Destroy a portion of Pa's worst nest by establishing new ones in various areas using Levy flights.

Step-8: Maintain the current optimal nest; if not, go to Step (2) Iteration (I) maximum iteration (I_{max}). Finally, determine the optimal solution. The optimization scheme is recognized by the hosts' probability of origin P_a [0, 1]. The appropriate weights for further processing are determined using the optimal outputs and the LASHP classifier. This optimization process is carried out at each layer of the LASHP and results in accurate processing.

Step-9: Obtain the resultant values from the step-8.

Step-10: Generate the secret key for manipulating the cipher policy for the data acquired.

Step-11: Apply the cipher policy with respect to the 512-bit sequential processing nature based on the key generated over the previous step, Step-10.

Step-12: Store the resultant cipher data to the remote server using internet services.

4. EXPERIMENTS AND RESULTS

This paper introduced a novel deep learning algorithm called LASHP with MCS security norms to predict healthcare metrics with enhanced security features. This approach is implemented using Python's powerful Artificial Intelligence processing Open-Source tool. The resulting emulations are clearly illustrated in the following summaries with graphical representations.

4.1 Datasets

This dataset was developed by integrating previously accessible but unrelated datasets. This dataset combines five heart datasets over 11 common characteristics, making it the biggest heart disease dataset accessible for study. It has 76 properties, including the anticipated one, but all reported tests use just 14. The "target" field indicates the patient has cardiac disease. 0 = no illness, 1 = disease. Every dataset used can be found under the Index of heart disease datasets from UCI Machine Learning.

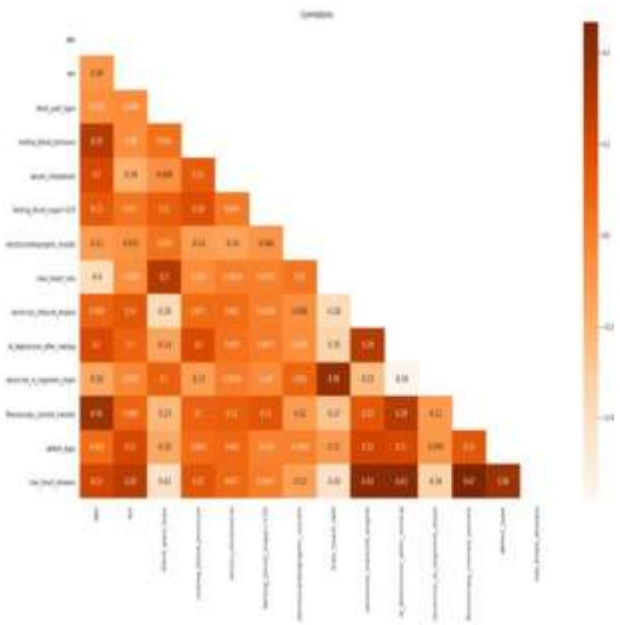

Fig.3 Dataset Content Quantity and Field Representation

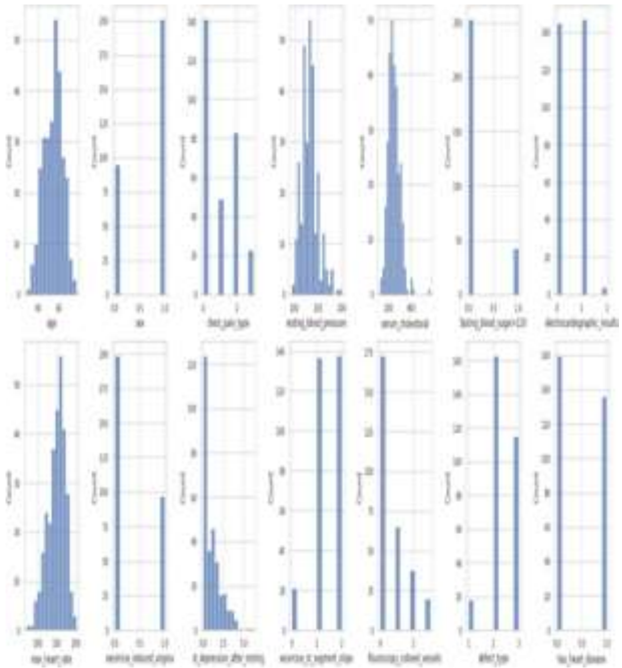

Fig.4 Field Count in Histogram View

The following figure, Figure 5, illustrates the perception of the proposed approach prediction efficiency to identify the heart defect type. It is based on the age factor and the associated metrics. The following figure, Figure 6, illustrates the perception of the proposed approach confusion matrix. It portrays the predicted and actual result ratio based on the loaded training model.

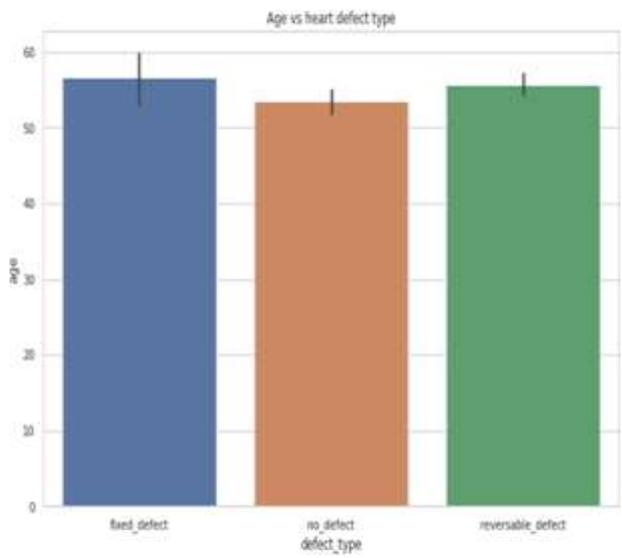

Fig.5 Heart Defect Type Analysis w.r.t Age Factor

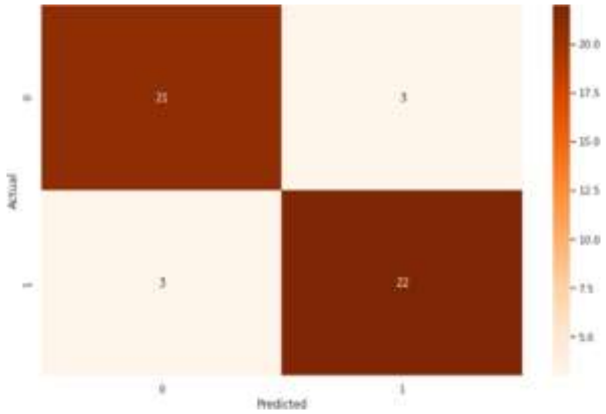

Fig.6 Confusion Matrix

The following figure, Figure 7, illustrates the perception of proposed approach weight definitions based on the factors considered for manipulating the features associated with the dataset. The following figure, Figure 8, demonstrates the perception of the proposed approach Region of the Curve (ROC) graph. In addition, it portrays the resultant view based on the actual favorable and false-negative rates.

Weight	Feature
0.0857 ± 0.0305	typical_angina
0.0694 ± 0.0986	0_flouroscopy_coloured_vessels
0.0490 ± 0.0490	st_depression_excercise_after_rest
0.0367 ± 0.0476	reversable_defect
0.0327 ± 0.0200	serum_cholestoral
0.0204 ± 0.0516	resting_blood_pressure
0.0163 ± 0.0305	excercise_induced_angina
0.0163 ± 0.0305	non_anginal_pain
0.0163 ± 0.0305	normal_st_waves
0.0122 ± 0.0200	1_flouroscopy_coloured_vessels
0.0122 ± 0.0200	sex
0.0122 ± 0.0200	flat_st_slope
0.0041 ± 0.0163	3_flouroscopy_coloured_vessels
0.0041 ± 0.0305	no_defect
0.0041 ± 0.0305	left_ventricle_hypertrophy
0 ± 0.0000	negative_st_slope
0 ± 0.0000	atypical_angina
0 ± 0.0000	elderly
0.0000 ± 0.0258	positive_st_slope
0 ± 0.0000	fixed_defect
0 ± 0.0000	fasting_blood_sugar>120
0 ± 0.0000	st_wave_abnormality
-0.0041 ± 0.0163	2_flouroscopy_coloured_vessels
-0.0041 ± 0.0163	asymptomatic
-0.0163 ± 0.0476	max_heart_rate

Fig.7 Weight Definitions based on Dataset Features

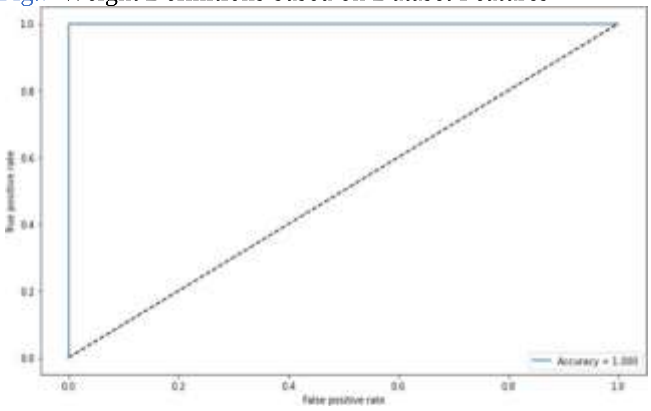
Fig.8 ROC Curve

The following figure, Figure 9, illustrates the perception of the proposed approach resulting in accuracy with proper graphical specifications, in which it attains the resulting accuracy of 98.18%, as well as the accuracy ratio, is cross-validated with the conventional learning technique called Artificial Neural Network to prove the efficiency of the proposed approach in detail.

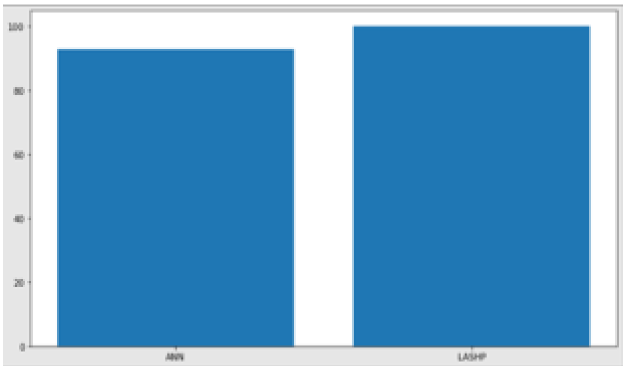

Fig.9 LASHP Accuracy Analysis vs. ANN Accuracy

5. CONCLUSION AND FUTURE SCOPE

This paper offers a real-time healthcare analysis system based on Learning Assisted Secured Health Prediction (LASHP) and Modified Cipher Scheme (MCS). The method comprises two major components: it detects the final layer of the proposed LASHP deep learning logic based on neural network strategy. Then, it deletes it using the delete function provided by the SFS principle. Finally, it incorporates classification logic over the final layer to distinguish the proposed reason from ANN. The system not only makes full use of the cloud layer's real-time nature but also of the deep learning layer's computational solid capacity.

Additionally, we studied the identification of cloud layer anomalies using a Deep Learning-assisted network model. The suggested technique has a prediction accuracy ratio of 98.18%. In the future study, we will analyze how to increase the diagnostic rate of aberrant detection. This may be accomplished by incorporating specific sophisticated classification models, such as Random Forest (RF), into the proposed system and utilizing attack-finding skills to identify anomalies.

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