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RESEARCH ARTICLE

Smart Patient Monitoring and Recommendation (SPMR) Using Cloud Analytics and Deep Learning

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ABSTRACT The escalating global prevalence of chronic and lifestyle-related illnesses presents substantial societal and economic challenges. This work delves into an extensive review of healthcare monitoring systems tailored for chronic and lifestyle disorders. Subsequently, we propose a pioneering Smart Patient Monitoring and Recommendation (SPMR) framework, leveraging Deep Learning (DL) and cloud-based analytics. SPMR ensures continuous monitoring and predictive insights into a patient's authentic health status using data from vital signs and contextual activities collected via Ambient Assisted Living devices. Within the predictive DL component of the LIP module, we employ Categorical Cross Entropy (CCE) Optimization to forecast real-world health conditions using unbalanced datasets derived from Chronic Blood Pressure Disorder case studies. Significantly, SPMR's capability to deliver real-time preventive measures and treatments persists even without Internet or cloud connectivity. This circumvents the need to replicate Machine Learning (ML) models and associated procedures in local setups, thus streamlining operations. Comparative analysis against analogous models showcases the considerable effectiveness of our proposed model, notably enhancing accuracy by up to 8 to 18 percent. Moreover, both the overall F-score and the emergency class F-score exhibit marked improvements of 17% and 36%, respectively. These outcomes underscore SPMR's pivotal role, especially during crises, emphasizing its significance in healthcare monitoring systems.

INDEX TERMS Remote patient surveillance, chronic diseases, ambient assisted living (AAL), predictive deep learning, IoT, healthcare, machine learning, deep learning.

I. INTRODUCTION

The latest information from 2016 reveals that diseases like cardiovascular disease (CVD), chronic kidney disease (CKD), cancer, chronic respiratory disease (CRD), diabetes, and others are responsible for almost 71% of all deaths globally [1]. This has led to increased healthcare expenses and a shortage of caregivers due to the growing number of elderly individuals [2], [3], [4]. Fortunately, advancements in medical technology, such as mobile communication, Wireless Sensor Networks (WSNs), Internet of Things (IoT), big data, and wearable computing, have

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brought breakthroughs in the healthcare sector [6], [7]. Monitoring patients' vital signs remotely through a Wireless Body Area Network (WBAN) is seen as a new and effective approach that doesn't affect patient mobility [8], [9], [10]. Smart IoT devices, communication-enabled sensors, and other technologies are assisting hospitals in better understanding their medical equipment, physicians, personnel, and patients [11], [12], [13]. Various studies have explored different aspects of remote healthcare and monitoring, addressing prerequisites, data-driven healthcare philosophy, and the use of AI and DL techniques like transfer learning for processing medical data [14], [15]. These advancements enable data scientists to employ predictive analytics based on Machine Learning (ML) to improve health outcomes, manage sickness progression, and identify disease causes by analyzing real-time patient assessments, symptoms, history, surroundings, and vital signs [16].

Aside from activities such as sleeping and exercising, environmental factors such as temperature and humidity have an effect on a patient's vital signs [17]. A big rise in heart rate (HR) during exercise, for example, is not abnormal, but an excessively high HR in a patient is. Other factors that may affect a patient's vital signs include their age, behaviours, and gender, to name a few [18]. They all emphasise the significance of context awareness and vital signs, which might signal a patient's health status and so allow for more personalised healthcare and services [18].

The vital signs of patients and other data obtained via the continuous monitoring of Ambient Assisted Living (AAL) devices provide a diverse collection of Big Data [19]. Real-time action is essential when dealing with massive data quantities [20]. Numerous machine learning (ML) models have been built to enhance analytics and predictions using smart patient monitoring systems, but they have not yet been assessed outside of their native setting [21]. We may claim that the majority of the models are not based on patient situations and simply label the disease as "Yes" or "No." Due to their focus on accuracy, these models may provide erroneous findings when compared to datasets with imbalances [22]. In addition, category accuracy and F-scores for certain classes have been fully deleted from modern multiclass models.

Due to its reliance on a local server and a single illness, all previous Remote Patient Monitoring (RPM) systems are unable to handle a patient's severe condition or seek emergency assistance. Moreover, none of these systems are able to manage enormous quantities of data or context [23]. Consequently, academics have devised AAL systems that consider context [24].

Additionally, cloud computing (CC) platforms are required for improved analytics and forecasting in the large amounts of data generated by intelligent RPM systems [25], [26]. Scalable computer resources and the most recent technology are combined in these cloud platforms to increase efficiency and save costs. There have been new proposals to support RPM with a cloud-based architecture capable of handling massive amounts of data [27]. When compared to other previously suggested designs, these architectures only use cloud-based systems. This means that the cloud-based model is completely responsible for classifying a patient's health state, which poses a risk to the patient if the Internet connection is lost [28].

In this comprehensive examination, the paper navigates through the landscape of healthcare monitoring systems, encompassing both IoT and ML-based approaches, establishing their prevalence and smart functionalities [29], [30], [31]. A meticulous review and comparison of contemporary research materials are presented in Table 1, providing insights into the existing landscape. Recognizing the challenges and limitations of prior systems, the paper introduces a novel framework known as Sensory Perception Monitoring and Response (SPMR). The SPMR framework, rooted in Deep Learning (DL) and Cloud-oriented analytics, addresses the complexities associated with accurate predictions and classifications of patients suffering from chronic illnesses [32], [33], [34], [35]. Notably, the integration of cloud analytics and DL technologies within SPMR aims to substantially enhance the accuracy and efficiency of patient monitoring, ensuring real-time predictive insights into a patient's authentic health status. Moreover, SPMR's versatility, equipped with IoT, ML, Cloud Computing, and AI-enabled devices, positions it as a forward-thinking and adaptable solution, providing comprehensive healthcare monitoring that overcomes the challenges associated with traditional Remote Patient Monitoring (RPM) systems.

Two pivotal motivations underscore the significance of SPMR: firstly, the escalating global prevalence of chronic and lifestyle-related illnesses demands sophisticated monitoring solutions; secondly, the integration of cloud analytics and deep learning technologies aims to enhance the accuracy and efficiency of patient monitoring. SPMR, equipped with IoT, ML, Cloud Computing, and AI-enabled devices, emerges as an adaptable and forward-thinking approach in healthcare monitoring [36], [37].

The following are the study's primary goals:

- Identify a patient's critical condition from a distance using vital signs and medical rules with active contexts.
- Assess the real-time health status of patients with chronic diseases who are monitored by healthcare professionals and Ambient Assisted Living (AAL) devices using more efficient models.
- Handle Big data analysis in unstructured and unbalanced datasets using the proposed models in this paper.
- Compare models that categorize locally and in the cloud to see which ones are more effective.

This is how the remainder of the document is organized. Section II of this research presents the SPMR framework and DL approach for local and cloud predictive models (CPM). Section II content literature review summary.

The algorithm and mathematical model for new CCE optimization are also covered in Sect. III. Patients with

TABLE 1. Monitoring patients with chronic diseases: a review of healthcare regimes.

Features	[1]	[3]	[8]	[16]	[20]	[21]
Issues that have been addressed	Chronic kidney disease (CKD)	Diabetes	Diabetes diagnosis	Temperature and pulse	Blood-pressure disorders	Chronic diseases
Architecture	Cloud-based hybrid (4-tier)	Zion China Architecture	3-tier	WSN and IEEE 802.11 are the foundations of this system.	A hybrid architecture that includes both local and cloud-based components (3-tier)	two-tier (Client and Cloud side)
Experiment domains	Cloud computing, Machine Learning	IoT, Machine Learning, and Cloud Computing	Big Data, IoT, Cloud, and Machine Learning are all terms used to describe the Internet of Things.	Internet of Things.	IoT, Machine learning, and cloud computing (three tiers)	Analytics, IoT, and cloud computing
Reliability	Low	High	High	Low	High	High
Tools for ensuring reliability and the environment in which they are employed	CloudSim package Windows Azure	Business intelligence, Azure ML, SQL	5.0 generations of wearable technology, 5G networks	Sensors and Raspberry Pi 3	Weka Spark package and MATLAB R2016b (9.1)	Amazon EC2
Functionality (Prediction/ Classification/Monitoring/Analysis)	Classification	Prediction	Evaluation as well as Forecasting	Sense-making and Keeping an Eye On	Classification	Monitoring and Analysis
Exhibited items	Static	Dynamic	Environmentally responsible and economical	Stable	Context-aware	Static
Advice and suggestions	No	No	Yes	No	No	No
Cost	Low	Low	Low	Low	High	It's about right.
The difficulty of it all	Low	High	High	Medium	High	It's about right.
Parameters	Measures of Accuracy and F, as well as Error Rates	Normal glucose levels were detected.	Accuracy	The correctness of reading	Time, F-measurement Accuracy, and Precision	Accuracy of the ECG
Dataset size	Extremely tiny (306)	Large	Small	Small	MATLAB was used to produce a large dataset.	Huge
Efficiency results (Accuracy)	up to 97%	up to 87%	up to 92%	up to 95%	76–99%	up to 91%

chronically high blood pressure will be monitored using the experimental set-up described in Section IV. As a comparison to earlier investigations, the experiments in Section V present and discuss numerous performance measures. Section VI presents the findings and recommendations for future research.

II. LITERATURE REVIEW

There are a number of benefits to using an Internet of Things-enabled remote health monitoring system instead of conventional methods. The device's capacity to convert analog information into digital form opens the possibility of continuous monitoring for the patient. This facilitates self-care on the part of patients and permits the detection of chronic illnesses at an earlier stage. Several relevant research articles are summarized here.

Qureshi et al. [38] provide an account of their efforts to conceptualize WIoT from a technical, organizational, and logical standpoint in relation to wearable devices. There are typically three parts to an IoT architecture for wearables. 1) People can wear sensors on different regions of their body. Through Gateways connected to the Internet, the data acquired by the sensors may be sent to the server or cloud for storage and analysis. Thirdly, cloud computing and IoT connectivity may facilitate machine learning and big data analytics. Darshan et al. address the function of IoT in healthcare and do a literature review on the topic. Their proposed system has many levels: a) raw data is supplied and gathered from different sensors on medical IoT devices (ECG sensor, EEG sensor, skin temperature sensor, etc.). Here, we take the information that has been filtered, processed, and categorized and use it to do analysis and make predictions. Sahoo et al. [39] present an introduction to the Internet of Things, its past and future, and how it relates to healthcare. The concept of the Internet of Things evolved from Electronic Data Interchange (EDI) in 1999 into the Internet of People (Internet, M-Internet), and is now its own distinct entity. The IoT not only benefits us personally but also many different businesses. They advocate for implantable medical devices that connect to the Internet, medical professionals, and patients as part of healthcare delivery.

When it comes to e-health and the Internet of Things, Wong et al. [40] provide a paradigm for intelligently providing medical services. The following are the stages of the proposed Internet of Things-based paradigm: The four main components of telemedicine are: A) Patient Records, which contain all data regarding the patient, acquired in real-time or from a dataset; B) Clinical Decision System, which provides DSS for the physicians based on connected knowledge; C) Remotely monitoring the patient through the use of sensors attached to the human body to collect data; and D) Remote treatment, a crucial step because it facilitates contact with healthcare centers by easily, that gives the rural population better healthcare. Cano-Marin et al. [41] provide the idea of how the Internet of Things (IoT) contributes to and enhances healthcare facilities. There are three tiers to the suggested system, the first of which is for sensing, which is the process of gathering data or information in real-time using sensors (temperature sensor, pulse rate sensor, etc.). The second level of transmission involves sensors sending their collected information to a data server. The doctor may view patient information and make diagnoses from inside the server with Tier-3 access. The suggested work consists of both digital (an Android app and a web page) and physical (an ATMEL 89s52 microcontroller, temperature sensor, pulse rate sensor, serial port, A/D converter, and IC-7805 voltage regulator) components. Yang [42] offers a comprehensive review of IoT's potential in healthcare. He talks about innovative approaches of providing healthcare, such as mHealth and 6LoWPAN-based healthcare. The mHealth framework consists of three main parts: 1) The Layer for Collecting Data There is a layer 2 for storing data and a layer 3 for processing it. The first step of a 6LoWPAN-based healthcare system is for sensors to collect data, and then the gateway would convert the data to IPV6 and send it to the server. They go on their talk about the latest complete architecture for healthcare smart systems.

Individuals with chronic diseases like stroke, diabetes, cancer, etc., may efficiently monitor their own health with the help of a healthcare monitoring system developed by Faisal et al. [43], which makes use of the Internet of Things (IoT) and classifier algorithms for prediction. The suggested method for monitoring stroke patients consists of three parts: 1) The hardware tier consists of the microcontroller, blood pressure monitor, and glucose analyzer. Finally, at the application layer (web environment, cloud server), machine learning (ML) techniques such as Naive Bayes and Random Forest are deployed. The predictive accuracy of the Random Forest algorithm is 93%. In [44], Horani et al. propose an IoT-based cancer care system hosted in the cloud. The method used in this research involves attaching a body wireless sensor network (BWSN) to a patient and then collecting and converting data through the Zigbee protocol before saving it to a data set or the cloud for analysis. Conceptually, the Internet of Things (IoT) and its multi-tiered architecture 1) The patient is outfitted with a network of sensors that are permanently attached to his or her body. 2) A management processing layer that acts as a conduit for information remapping. Fourth, the applications layer is where the action is on the Internet of Things since that's where all the cool stuff occurs, including information processing, analytics, security, and device administration. The challenges associated with implementing IoT in healthcare systems were analyzed by Maruyama et al. [45] and discussed further.

IoT-based healthcare monitoring system architecture proposed by Kapoor et al. [46] uses ML algorithms to identify early warning symptoms of heart illness. The suggested system consists of three levels: At the first level, data is acquired via Internet of Things sensors carried by the user. Level 2 uses Apache HBase to store petabytes of information. Level-3's data analytics skills are particularly useful in the field of cardiovascular disease forecasting. Machine learning algorithms (MLA) are implemented here. The results produced by the system are clearly superior. As suggested by Rathore et al. [47], ensuring security via the use of IoT and cloud computing. Fuzzy Rule is an innovative approach to diagnosing various diseases that they present. There are a total of eight parts that make up the suggested system. These parts include medical sensors, the UCI Repository Dataset, cloud computing, data aggregation, a fuzzy temporal neural classifier, and more. The code was written in JAVA, and Amazon's cloud servers hosted the finished application. K-NN, DT, NB, and SVM are four of the most common classifiers used in medical diagnosis. The final results are as follows: K- NN achieves 92% accuracy, DT achieves 95% accuracy, NB achieves 85% accuracy, and SVM achieves 80% accuracy.

Roderick et al. [48] describe the intelligent technique for student diagnostics. Here are the proposed steps for the planned three-stage procedure. 1) Collecting data from IoT gadgets. The gathered information is sent through a gateway to a secondary cloud-based system. Second, a diagnosis must be made once the data has been processed, features extracted, healthcare measures extracted, measured, analyzed, and so on. Finally, the patient's loved ones get a health alert. As classifiers, they use DT, k-NN, NB, and SVM.

Based on the literature review provided, the conceptual methodology in the paper is built on a strong foundation, drawing insights from various studies on Internet of Things (IoT) applications in healthcare. The literature review extensively covers the use of IoT in healthcare, addressing areas such as wearable devices, remote health monitoring, telemedicine, and the role of IoT in managing chronic diseases. The studies cited demonstrate the multi-tiered architecture of IoT systems, involving data acquisition through sensors, transmission to servers or the cloud, and utilization of machine learning algorithms for analysis. Various healthcare monitoring systems are discussed, showcasing applications for chronic diseases like stroke and cancer. These systems often leverage classifier algorithms and IoT technologies for effective prediction and monitoring. Security considerations in IoT-based healthcare systems are highlighted, emphasizing the need for secure data transmission and storage. Innovative approaches like fuzzy rule systems are introduced for disease diagnosis. The literature review underscores the versatility of IoT in healthcare, covering diverse applications such as cardiovascular disease forecasting, student diagnostics, and early warning systems for heart illnesses.

In the process of selecting our final model for ''Smart Patient Monitoring and Recommendation (SPMR) using Cloud Analytics and Deep Learning,'' we conducted rigorous testing across various models and schemes. Our testing phases involved a comprehensive evaluation, considering critical factors such as reliability, functionality, cost, and efficiency. We drew insights from a comparative analysis, leveraging a detailed examination of healthcare regimes presented in Table 1.

The testing criteria included parameters like accuracy, precision, F-measurement, and error rates. We thoroughly examined the exhibited features, architecture, experiment domains, reliability, tools employed, functionality, advice and suggestions, cost, difficulty, parameters, dataset size, and efficiency results from the reviewed healthcare regimes. By systematically analyzing these aspects, we aimed to ensure that our chosen model not only met high standards of reliability and functionality but also aligned with the specific requirements of patient monitoring in the context of chronic diseases. This thorough testing approach allowed us to make an informed decision in selecting the most suitable model for our research, contributing to the robustness and effectiveness of the proposed SPMR framework.

III. SPMR PROPOSED ARCHITECTURE

AI-enabled, IoT, deep learning, and cloud computing gadgets have all found a home in modern healthcare facilities. Patients with chronic conditions can benefit from these hybrid technologies, which provide improved patient monitoring and referral systems. The SPMR framework allows hospitals and caregivers to provide better home care for patients. A DL model applied to vital signs and context data helps to acquire, store, monitor, and forecast the patient's health state. In Fig. 1, you can see the proposed SPMR's four-layer architectural structure. Sects. III-A–III-D describe the various layers.

A. AMBIENT ASSISTED LIVING LAYER 1 (AAL)

Define Patients' vital signs and environmental conditions can be monitored and recorded using the AAL system and open-source e-health software such as My Signals [29].

(Humidity and Temperature). Additionally, AAL systems always keep track of the patient's whereabouts and activity. Each AAL system has a distinct identifier within the cloud architecture. The patient's condition determines which devices are chosen. E-health systems support an extensive array of connectivity options and specialized medical sensors. A support system for sensors that detect light, smoke, temperature, and humidity is provided by the AAL layer. A layer that monitors key signs while simultaneously recording the surroundings around it.

B. LOCAL INTELLIGENT PROCESSING AT THE SECOND LAYER (LIP)

The LIP module collects, aggregates, stores, and processes data that is sent over intermediate communication protocols and makes it available to the rest of the system. Because of this, it may be used both in offline and online environments. It differs from previous frameworks in that it offers high-performance offline learning and recommendations. It includes the following parts:

1) EDGE DEVICE

IoT Gateway is another name for this device. Low-level data from sensors, intelligent devices, and the cloud can be exchanged and processed locally using hardware or software.

2) AN ON-SITE LOCAL PROCESSING AND STORAGE FACILITY UNIT (LPSU)

An appropriate format is used to store and transform the AAL layer's data for the DL model in LPSU. This unit is also responsible for transforming features. Data exploration is carried out using a variety of strategies, including normalization. LPM receives the reworked components. Also, the LPSU has a Cloud Monitoring Module that updates the general medical rules and medical records on a regular basis (CMM).

3) THE SUGGESTED LOCAL PREDICTIVE MODEL HAS THE FOLLOWING CHARACTERISTICS: (LPM)

Patients' health status and emergency scenarios are classified by LPM on the local side. The model in [30] downloads the model from the cloud, in contrast to this unit. Vital signs and current AAL data are used to develop the LPM unit's own categorization and prediction model. In the event of a network outage, a lack of cloud services, or any other type of emergency, the model will hold. Once the patient's health state has been accurately assessed, this layer takes the required and appropriate steps to contact medical professionals, caretakers, or other support services. The diagram in Fig. 2 provides an overview of the LIP model development and prediction process utilizing DL based on new CCE optimization. Sect. III-E provides a thorough explanation of the algorithm in use.

C. CLOUD MONITORING MODULE IS LOCATED IN LAYER 3. (CMM)

The term ''knowledge module'' refers to the CMM as a unit of information. Clouds with patient-specific information, assistance services, and knowledge databases are part of the package. Two or more clouds can be included in the CMM if the right permissions are obtained. When allowed and

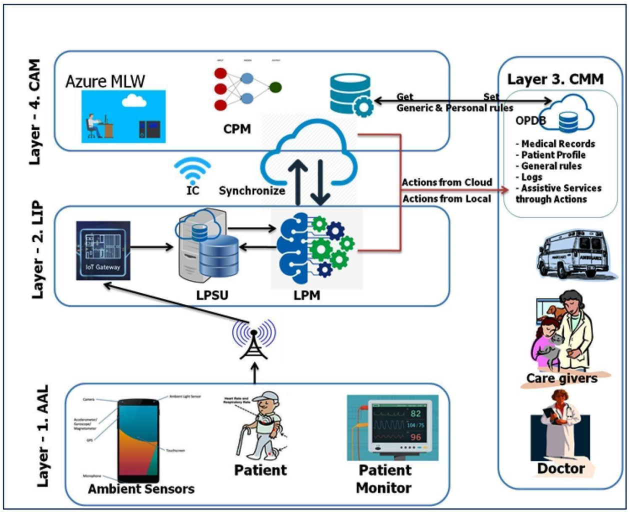

FIGURE 1. Framework components and the proposed architecture of Smart Patient Monitoring and Recommendation (SPMR).

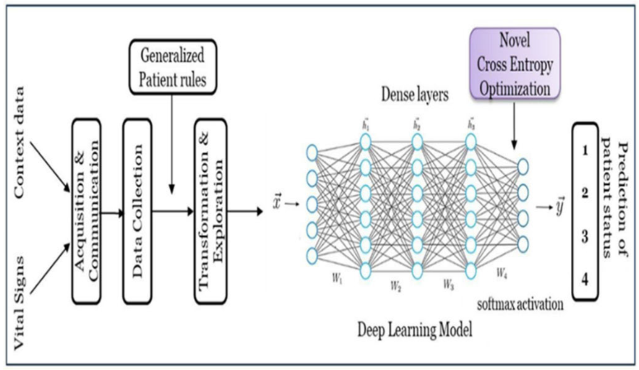

FIGURE 2. Proposed LPM (Lifestyle Prediction Mechanism) prediction mechanism.

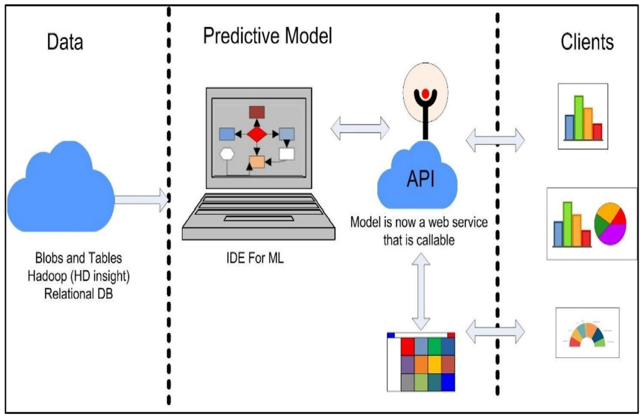

FIGURE 3. Predictive models built and deployed using the Google Cloud Platform ML service.

linked to these clouds, SPMR monitors the CMM. Medical specialists, hospitals, and carers are all involved in providing assistance. The most important aspects are covered here.

1) ONLINE PATENT DATABASE (OPDB)

Information on the patient, such as age, sex, and weight, can be found in the OPDB. This program is also responsible for keeping track of a patient's medical records and investigation results, as well as their treatment and assistance plans, food, and any specific thresholds for vital signs. An OPDB cloud storage account is provided and monitored by a smart healthcare center or hospital. When it comes to patient-specific regulations and updates, OPDB and the medical cloud are in sync [31], [32].

2) (MC) THE MEDICAL CLOUD

Symptoms, vital signs to monitor, and broad rule ranges are all included in this cloud of current medical knowledge. Medical knowledge is based on the most recent studies and generic norms in MC, which are updated regularly. The OPDB syncs up with this information.

3) ASSISTIVE SERVICES

Services supplied by a smart healthcare facility or hospital are also included in this category. Also included in this is the patient's family, friends, and caretakers. When a patient's health began to decline or an emergency occurred, these services were activated. The LIP and CAM layers send alerts to the team, which responds remotely to any issues that arise.

D. CLOUD FOUR LAYERS OF MONITORING AND CLOUD ANALYTICS PROPOSED (CAM)

Physically situated cloud components that adhere to strict privacy standards and legislation can be found in this tier. The massive amounts of data generated by AAL are housed on massive cloud infrastructure. It's also accessible as a subscription service on several platforms (Software as a Service). To meet the needs of large data analysis, this framework was developed on an expandable cloud platform and is fast, efficient, and accurate [33], [34]. Together with layers 2 and 3, this layer accumulates the preceding two levels' data and rules. The CAM-administered machine learning model can analyse massive amounts of data and trends in order to anticipate a patient's health status. The GCP (Google Cloud Platform) Cloud Predictive Model (CPM) is included in this module and may be accessed online. The model's inputs and outputs are synchronized by layer 2, which is the second layer. The following components are included in this module:

1) WORKSPACE FOR GCP MACHINE LEARNING (MLW)

To speed up prediction and classification, GCP-MLW [35] stores and distributes computation over many computer clusters. Machine learning models may be built and deployed using this programmed. ML Gallery, ML Studio, and Management of ML Web Services are all included in Microsoft's ML Workspace.

2) TO HANDLE LARGE DATA SETS, THE PREDICTIVE MODEL (CPM) IS IMPLEMENTED USING GCP MACHINE LEARNING (ML)

There are typically five key steps to knowledge discovery using CPM: preprocessing, model training, testing and evaluating, and finally deployment. Microsoft's GCP ML platform covers all aspects of machine learning. The ML model was built and deployed using GCP's ML service. Packages and APIs for building machine learning models are available through the GCP ML service, which may be used to construct web and mobile apps using these models. Figure 3 depicts the use of the GCP ML service for the development and deployment of a predictive model.

E. SPMR'S SUGGESTED DL TECHNIQUE FOR LPM AND CPM

In the higher layer, AAL sends all of the recorded data. For the purposes of LPM and CPM, data are gathered, aggregated, stored, and analyzed in LIP. Predictive models are designed to demonstrate the most accurate categorical categorization accuracy for the benefit of patients and healthcare providers. The data has been processed using the technique shown below. The stages of the model development process are outlined in the following paragraphs.

1) DATA GATHERING AND AGGREGATION

Unstructured data gathered from sensors and offline devices, alongside data obtained via the MySignals platform, is captured and buffered by the Edge device, according to SPMR. On the edge, raw data may be translated from a low-degree to a higher-degree abstraction using the High-Level Feature Provider (HLPF), also known as the Context Aggregator [37].

Note: Notations for below Algorithm

Input dataset with features ***1*** to ***n***:

$$A = a_1, a_2, \ldots\ldots\ldots\ldots a_n$$
$$W^1 = w^1, w^1, \ldots\ldots\ldots\ldots w^1$$

W^h : represents weight set at layer ***h***

W^1 : represents weight set at first hidden layer.

f ( ) is a step function.

***f* (Z)** is activation function

$$h_j^i = f(Z)$$

The activation function used in hidden layers is rectified liner unit "relu".

- Output of linear equation = **Z**
- bias = **b**
- attribute value = **a**
- total number of features = **n**
- number of features extracted = **m**
- mean of training samples = α
- standard deviation of training samples = σ

represents i^{th} neuron in i^{th} hidden layer.

The superscript i represents layer while subscripts represent neuron number.

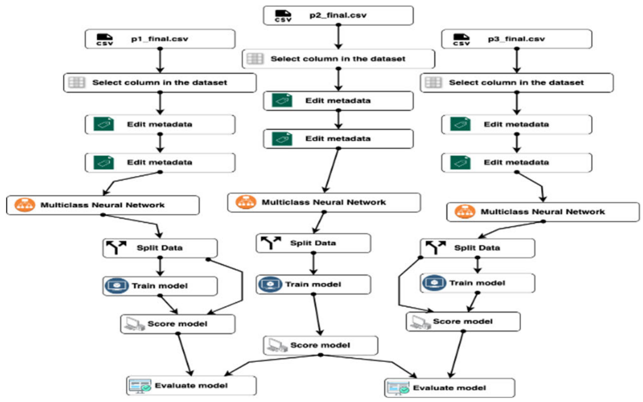

FIGURE 4. Phases of (CPM) Cloud Predictive Models (DL) implementation on the GCP cloud.

Number of classes = **k**

$\hat{y}$ is probability set for $\{y_1, y_2, y_3, y_4\}$ class labels i.e, Normal, Alert, Warning, and Emergency.

softmax (Z)compresses the vector [Z] containing real values into real values within the [0,1] range, ensuring their sum totals 1.

Where μ_i is proposed individual Cross Entropy (CE)

2) PREPARATION OF DATA FOR ANALYSIS

Once the MySignals kit and HLFP data is converted into a unified contextual state by the LPSU, it is stored in a data repository. Data in the 'csv' format relating to the patient's physiological signals, environmental circumstances, and activities are included inside this section for the duration of the time period indicated. Numbers are used to represent both numerical and categorical data in DL models. As a result, the data are transformed into a numerical representation that is compatible with the DL model used in LIP and CAM.

Additionally, the z-score normalization technique was employed in this study to standardize (normalize) the data. Each neuron in a Deep Neural Network (DNN) conducts arithmetic operations on the inputs and weights it receives.

3) TRANSFORMATION OF DATA

After the pre-procedure assessments are complete, the numerical value of an attribute is represented as a straightforward vector. If you've ever trained and operated a deep learning model using tensor transformation, then you'll know exactly what we're talking about here. Using this transformation, the model's features can be translated into the format that the model employs to make computations go more quickly and with less effort. A tensor is a representation of vectors and matrices in a higher dimension than they are traditionally used. Within its internal structure, TensorFlow encapsulates tensors by utilizing collections of elemental data types that are n-dimensional in dimension. Tensors have the capability of extracting the maximum amount of performance from the System's hardware. Primitives for optimal DL are also

Algorithm 1 DL algorithm for LPM amd CPM

Framework Inputs:

AAL data and Vital Signs

Model Phases:

Input:

$$A = a_1, a_2, \ldots\ldots\ldots\ldots a_n$$

I. Pre-process:

1. Convert types to numeric.
2. Apply **z - Score** for normalization:

$$z{-}score = \frac{a - \alpha}{\sigma}$$

II. Feature Engineering:

Extract features as per contexts

$$A = a_1, a_2, \ldots\ldots\ldots\ldots a_m$$

III. Model Building (Learn Phase):

1. Calculate

$$Z = \sum_{i=1}^{m} W_i^h A_i + b$$

2. Feed **Z** into ***f(Z),*** so that we get output at each hidden layer.

$$h_i^i = f(Z)$$

3. Calculate the probability score of class C_j given sample a_i.

$$P(C_j|a_i) = \frac{exp(Z_j)}{\sum_{k=1}^{4} exp(Z_k)}$$

IV. Test/Prediction:

$$\hat{y} = argmax_{j\epsilon\{1,2,3,4\}} P(C_j|a_i)$$

Apply softmax function at output layer

$$softmax(Z) = \frac{e^{Zi}}{\sum_i e^{Zi}}$$

V. Optimization:

Apply proposed CCE Optimization and calculate **E(W)**:

$$E(W) = -\sum_{i=1}^{k} \mu_i$$

Output:

$$\hat{y} = \{\textbf{\textit{Warning}}, \textbf{\textit{Normal}}, \textbf{\textit{Alert}}, \textbf{\textit{Emergency}}\}$$

supplied for things like Activations, Pooling, and Inner Products, among other things.

4) FEATURE ENGINEERING AND DESIGN

The Spearman's correlation coefficient is deemed more suited for healthcare data that includes outliers (emergency cases in our study) [38]. For this purpose, we used the metric Spearman's correlation coefficient to identify the most correlated of n characteristics from the n input features. The DL model has been given the tensors of the m correlated features. A multitude of disease-specific parameters, such as symptoms, vital signs, and so on, have been retrieved using the Spearman correlation coefficient for a variety of chronic illnesses. HR, DBP, SBP, RR, and symptoms were substantially linked with class designations in our research of BP patients.

We employed tenfold stratified cross-validation to deal with the unbalanced dataset based on the reference [39]. The F-score of the feature selection approach was 0.98. For consistency in the training and testing sets, k-fold stratified cross-validation assures an equal percentage of each class.

5) CONSTRUCTION OF A MODEL

In our pursuit of selecting the optimal model for "Smart Patient Monitoring and Recommendation (SPMR) using Cloud Analytics and Deep Learning," we conducted a thorough analysis, comparing key features and attributes across various healthcare regimes. Table 2. summarizes the review of different healthcare regimes, highlighting essential aspects such as issues addressed, architecture, experiment domains, reliability, tools, functionality, exhibited items, advice, cost, difficulty, parameters, dataset size, and efficiency results.

This comparative analysis helped us in selecting an optimal model based on rigorous testing and specific criteria, ensuring that our chosen model aligns with the desired attributes for effective patient monitoring in the proposed SPMR framework.

In NN, the output is determined by the input X and the weighted sum of the inputs:

$$Z = W^T X + b \tag{1}$$

Z stands for a linear equation, WT stands for weights, and b stands for bias. The step function predicts either a binary or multi-class output based on the value of Z. Discrete output is the term for this type of output.

Layers of computing are used to discover patterns from input data using the DL approach. Some information is taken at each layer, and the output of one layer is sent to the next [40]. In the realm of machine learning, it is recognized as a Deep Neural Network (DNN) and holds significance as a strong ML technique [41]. In order to predict a recurrent neural network (RNNs), convolutional neural networks (CNNs), and multilayer perceptron's (MLPs) are three popular designs that have been developed as part of Deep Learning. Their purpose is to determine the health state or sickness of a patient by studying the vital signs of the patient and the environmental stimuli that they are exposed to. Up to and including three tiers, SPMR's five-layer deep model learning procedure made use of an optimal parameter configuration (MLP). Phases of CPM for each kind of patient are presented in Figure 4 individually. The anticipated CCE optimization is described in Section III-F.

TABLE 2. A sample dataset of patients with high blood pressure.

Timestamp	DBP	SpO2	SBP	DBP	RR	HR	Act	Amb	L_Act	Symp	Med	Class
02-02-2019 00:00	74	98	111	74	12	66	5	0	5	0	0	1
02-02-2019 04:30	107	64	52	107	23	180	3	2	4	56	1	4
06-01-2019 03:30	118	92	159	118	13	105	3	0	3	6	0	3
06-01-2019 22:45	89	93	130	87	6	97	1	1	6	26	1	2

TABLE 3. Description of the data set background for three patients in the SPMR.

Normal	Class	Emergency	Alert	Warning	Total contexts
9307	(P1) Hypertensive	175	2404	23347	9307
19455	(P2) Hypotensive	148	1627	14003	19455
12517	Normotensive (P3)	109	1186	21421	35233

6) EVALUATION OF THE MODEL

The recommended models were meticulously constructed through the aforementioned procedures, specifically employing Deep Learning (DL) coupled with Categorical Cross Entropy (CCE) optimization. To comprehensively assess the models' efficiency, a real-world computing platform, Google Cloud Platform (GCP), was utilized. The evaluation process incorporated sophisticated techniques, including correlation-based feature selection and stratified sampling.

By leveraging a novel CCE optimization technique and harnessing the capabilities of cloud computing through GCP, the models demonstrated a remarkable capacity for conducting extensive data analysis, particularly on unstructured and imbalanced datasets. This approach ensures robustness and adaptability to real-world healthcare scenarios.

However, it is crucial to note that the datasets were not balanced using SMOTE or GAN. This decision was made to preserve the authenticity of the data and its representativeness of real-world scenarios. The inherent characteristics of the dataset and specific study objectives guided this choice.

The classifier, driven by patient data and contextual information, excels in predicting the patient's health status. The incorporation of false alarm minimization strategies ensures that the classifier achieves a balance between sensitivity and specificity, ultimately maximizing classification accuracy. This innovative classifier not only provides reliable predictions but also contributes to reducing unnecessary alerts, fostering a more efficient healthcare monitoring system.

Furthermore, the process of requesting assistance involves executing a set of well-defined procedures. This includes the seamless integration of patient data, the initiation of the predictive model, and the interpretation of the generated results. The meticulous implementation of these procedures ensures the accuracy and reliability of the system, laying the foundation for a robust healthcare support framework.

7) SECURITY MEASURES AND THREAT EVALUATION

In "Smart Patient Monitoring and Recommendation (SPMR) using Cloud Analytics and Deep Learning," the robustness of the proposed security measures is paramount. This section provides a comprehensive overview of the security measures implemented in the SPMR framework, emphasizing their effectiveness against potential threats.

- Encryption Protocols and Data Integrity: SPMR employs state-of-the-art encryption protocols to safeguard patient data during transmission and storage. The use of robust encryption algorithms ensures data confidentiality and integrity, preventing unauthorized access and tampering.
- Access Control Mechanisms: Access control mechanisms are implemented to regulate user access to sensitive healthcare information. Role-based access controls ensure that only authorized personnel, such as medical professionals and caregivers, have access to specific patient data, enhancing overall system security.
- Continuous Monitoring and Anomaly Detection: Continuous monitoring is a key aspect of SPMR's security strategy. The system incorporates anomaly detection mechanisms to identify and respond to unusual patterns or activities, alerting administrators to potential security threats in real-time.
- Offline Security Measures: Acknowledging scenarios without Internet or cloud connectivity, SPMR is designed to maintain its security measures offline. This feature ensures the framework's ability to deliver real-time preventive measures and treatments, even in emergency situations.
- Threat Evaluation and Countermeasures: A thorough threat evaluation is conducted to assess potential risks to the healthcare monitoring system. Countermeasures, both preventive and responsive, are implemented based on this evaluation to fortify the system against diverse security threats.

Algorithm 2 Optimizations for the CCE

Inputs:
Actual probability list (P)
Predicted probability list (Q)
Initialize the List of resulting cross entropy R and variables i, j and Mean_CE
for i to length (P):
  Calculate (CE) as [-sum ([P[i]∗log (Q[i])]
  Append CE for each input to lisr R
mean_CE = sum (R)/length (P)
for j to length (R):
  if (R[j] > mean_CE):
  R[j] = (R[j] - mean_CE)
Outputs: New CE obtained in list R

F. PROPOSED CCE (CATEGORICAL CROSS ENTROPY) OPTIMIZATION ALGORITHM

For the suggested DL, a unique CCE cost optimization is used. Our key aim is to minimize CCE losses in our model while using the entire training dataset. To build a fresh list of novel CCEs, the following algorithm is employed. As a result of the updated Cross Entropy (CE) values, Deep learning makes use of a number of different optimization strategies, some of which include stochastic gradient descent (SGD) and adaptive gradient descent (AdaGrad). could potentially lead to faster convergence. Average CE loss is calculated by removing the chance of an event that is much more likely than the average CE loss. When fewer epochs are used, the DL algorithms achieve their goal quicker [44], [45], [46].

Where log(), sum(), and length() are implicit function for corresponding function-alities

1) A MATHEMATICAL MODEL IS DISCUSSED IN DETAIL

After calculating the individual CE errors, first determine the mean CCE.

$$\mathrm{E(W)} = -1/\mathrm{N} \sum \_(\mathrm{i}-1)\hat{}\mathrm{k}\ \mathrm{y\_i}\ \log(\hat{}y\hat{}) \tag{2}$$

Compute Fresh CCE, E(W) based on μ_i where μ_i is new individual CE

$$\mu\_\mathrm{i}(3) = \mathrm{y\_i}\ \log(\hat{}\mathrm{y}\hat{}) - \mathrm{E(W)if\ y\_i}\ \log(\hat{}y\hat{}) > \mathrm{E(W)} \tag{3}$$

New CCE is based on the newer CE vector μ_i which may be expressed as:

$$\mathrm{E(W)} = -\sum \_(\mathrm{i}-1)\hat{}\mathrm{k}\mu\_\mathrm{i}$$

IV. SETUP EXPERIMENT

To test the credibility of SPMR and its constituent DL models, an experimental case study is offered here. Patients with persistent Blood Pressure (BP) issues can benefit from this study, which is currently being monitored. Patients with hypertension (P1), hypotension (P2), and normal blood pressure (P3) are all under observation [46], [47]

A. DATA CREATION USING FICTITIOUS INFORMATION

The scarcity of long-term monitoring data for patients with chronic diseases, such as high blood pressure, led to the creation of a dataset detailed in Table 4. Vital signs were collected at a 15-minute sample rate for a year from three actual patients, utilizing the PhysioNet MIMIC-II database [48]. Additionally, data from e-Medical IoT kits (My Signals) contributed to the creation of the fictitious dataset (S.L. 2019). SPMR, designed for context awareness, collects patients' physical activity and timestamps. In the CMM Layer, doctors and caregivers are responsible for determining and maintaining sensors linked to Ambient Assisted Living (AAL).

A year of vital signs, ambient circumstances, symptoms, activities, and medicine (Med) are collected by SPMR as a big data source, encompassing metrics such as heart rate, diastolic blood pressure (DBP), systolic blood pressure (SBP), respiration rate (RR), and peripheral oxygen saturation (SPO) are the vital indicators observed in this case study (SpO2). For long-term monitoring of biomedical data, synthetic data creation has demonstrated its dependability in earlier research [49]. Class descriptions for unbalanced datasets may be found in Table 4 (see below). General medical criteria can only categories the data into normal and abnormal categories since the dataset is so unbalanced. False positives result from this categorization, putting patients at danger of receiving the wrong medicine and care. With the use of SPMR, it is now possible to divide patients into several groups based on their activities, vital signs, symptoms, surrounding circumstances, and current drug intake.

According to personal medical guidelines, the circumstantial categorization in Table 5 is utilised to anticipate classes. In addition, it lists the activities that must be completed in order to meet the expected class's requirements. For a complete list of properties and ranges, please refer to Table 6.

B. SETUP OF THE EXPERIMENT ENVIRONMENT

Each trial was carried out on the same computer, which has the system comprises an Intel Core i3 processor clocked at 2 GHz and equipped with 8 GB of RAM. The software environment includes Python 3.7.7 and the necessary Python packages for machine learning, data mining, data visualisation, mathematical calculations, Additionally, graphics drivers are installed on a Microsoft Windows 10 (64-bit) operating system. The model's implementation relies heavily on Google TensorFlow and Keras (Keras Documentation). Using simple high-level APIs like Keras, TensorFlow is an open-source package that makes it easier to build and train machine learning models than ever before. From basic neural networks to high-level deep learning, the libraries include a wide variety of models (DL). For complicated nonlinear systems, the DL is the most effective of the ML models, making it the ideal choice.

For example, SciPy (1.1.0), Scikit-Learn (0.20.1), NumPy (1.16.2), Keras (2.2.4), TensorFlow Google (1.11.1), Pandas (0.23.4), and Matplotlib, Seaborn (0.9.1), were used to build the models (3.0.2). The local system is in charge of

TABLE 4. Classification based on the medical model and actions administered to the patient.

Action	Classification	Class
Call/SMS your doctor or physician to schedule an appointment and review your medical history.	A condition of alert or if more than two vital parameters are within the warning range; and (symptoms greater than zero, or medication is equal to 1)	Alert
There is no action.	All vital signs are within normal limits. In other words, there are Zero - (0) symptoms.	Normal
Send an alert to caretakers via Monitor or use SMS via phone	Any vital signs that are in the danger zone; or medication that is 1, or symptoms that are greater than 0	Warning
Call an ambulance, oxygen, a doctor, or anyone else who can help in an emergency.	More than two alert range vital signs and (symptoms greater than 0, or medication is equal to 1)	Emergency

TABLE 5. Description of the dataset's attributes, as well as their type and range.

Attribute Name and Symbol	Format/Type	Unit/Range
Vital Signs (SBP, HR, DBP, SPO2 and RR)	All Numeric	(50–230 mm/Hg, 30–220 beats/min , 30–140 mm/Hg, 40–100 (%) , 05–30 breaths/min)
Timestamp	"DD-MM-YYY HH:MIN" TimeStamp	02-02-2019 00:00 and 06-01-2019 00:00
Amenity circumstances (temperature room) (Amb)	All Numeric	Hot Normal Cold
A current activity and a previous one (L_Act and Act)	All Numeric	Eating Sleeping Household Walking Resting Exercising
Symptoms (Symp)	All Numeric	0–62
Class	Numeric/Categorical	Emergency Warning Normal Alert
Medication (Med)	Boolean Value	True (Taken) / False (Not Taken)

developing and deploying LPM at the layer 2 level. The model hosted on the cloud platform within 4th layer is built and deployed using GCPresources cloud and masters of labour welfare [50], [51].

V. DISCUSSION, COMPARISON AND RESULTS

In order to evaluate the performance of the suggested models in SPMR, many simulations were run with various optimization settings. Classifying and forecasting the patient's status using the DL + CCE based model in layer 2 is what is providing notifications to doctors, carers, and assistance agencies [52], [53], [54]. Layer 4's CPM uses DL and performs the same duties as the LPM. Both the local and cloud DL models' performance must be compatible in order to accurately determine a patient's health state and to provide appropriate recommendations to that patient. Therefore, this comparison includes both local and cloud-based models [55], [56], [57], [58], [59], [60].

Comparing DL + CCE with other classifiers developed in comparable and contemporary works is provided as well (see Table 7) [61], [62], [63]. The confusion matrix serves as the primary source of most of the data mining parameters. Fig. 5a–c depicts the CPM over cloud confusion matrix acquired for several classes, for all three patients.

In seeking avenues to further enhance the performance of the Smart Patient Monitoring and Recommendation (SPMR) framework, several strategies can be explored:

- Optimization Techniques: Continuously explore and implement advanced optimization techniques for Deep Learning (DL) models within the SPMR framework. Investigate alternative optimization algorithms or fine-tune existing ones to achieve even more efficient convergence and improved model performance.
- Feature Engineering: Conduct in-depth feature engineering to identify and incorporate additional relevant features that could contribute to better predictions. Consider contextual factors, patient behaviors, or lifestyle indicators that may provide valuable insights into health status, thereby enhancing the overall predictive capabilities of the system.
- Data Augmentation: Explore techniques such as data augmentation to artificially increase the size and diversity of the dataset. Augmenting the dataset with variations of existing instances may help mitigate data

TABLE 6. A comparison of this research to another recent study.

Ref	Experiment data	Findings	Results
[1]	Watermark embedding, feature extraction, hybrid logistic regression, and neural network architecture	Chronic Kidney disease factors	Accuracy = 97%
[8]	ANN, SVM, and Ensemble are all examples of machine learning techniques.	Data on physiology and context	Accuracy = 92%
[14]	Perceptron with Multiple Layers (MLP)	Vital statistics Monitoring the context with AAL systems	Accuracy on average = 92.58 percent FPR for P1 equals 0.117; FPR for P2 equals 0.025; and FPR for P3 equals 0.095.
[20]	Methods of sampling; Ensemble; Nave Bayes (NB) + SMOTE; SVM + SMOTE	Data on vital signs in context	Accuracy of NB + SMOTE = 92.5 percent Accuracy of SVM + SMOTE = 84.4 percent
[21]	One-class support vector machine (OCSVM)	Vital parameter sign Monitoring of the ECG	Accuracy = 91%
Our Purposed	Deep learning prediction Optimization of categorical cross entropy in a novel way	AAL systems collect vital signs and patient context data.	F-score (Emergency) = 0.91–0.97 DL + Novel CCE (patient side): Accuracy = 99.93% Accuracy = 99.96% F-score (Emergency) = 0.9–0.97

imbalance issues and further enhance the robustness of the predictive models.

- Ensemble Models: Investigate the implementation of ensemble learning techniques, where multiple models are combined to make predictions. Ensemble models can often outperform individual models by leveraging diverse strengths. Combining the Local Prediction Module (LPM) and Context Prediction Module (CPM) in an ensemble approach may yield improved forecasting accuracy.
- Dynamic Model Updating: Implement mechanisms for dynamic model updating based on continuous learning. As new data becomes available, the models could be updated in real-time, ensuring that the SPMR system remains adaptive to evolving patient conditions and healthcare scenarios.
- Adaptive Thresholds: Explore the establishment of adaptive thresholds for urgency classifications. Fine-tune the sensitivity and specificity thresholds based on the specific health conditions or characteristics of individual patients. This customization can contribute to more precise and tailored alerting mechanisms.
- Integration of External Data Sources: Consider integrating external data sources, such as real-time weather data, air quality information, or other environmental factors, to enhance the contextual understanding of a patient's health. This integration could provide a more comprehensive view and contribute to improved forecasting accuracy.
- Continuous Monitoring and Evaluation: Establish a robust system for continuous monitoring and evaluation of model performance. Implement feedback loops that allow the system to learn from outcomes, identify areas for improvement, and adapt over time.

By exploring these avenues, the SPMR framework can not only maintain its high performance but also evolve to meet the dynamic challenges of healthcare monitoring, ensuring continuous improvements in accuracy, efficiency, and adaptability.

A. PERFORMANCE METRICS

Predictive models are evaluated based on the factors that best identify their predictive models Precision, F-measure, and Categorical Precision are the best metrics for assessment. An essential indicator for model comparison and demonstration of efficacy is the F-score (average) and the F-score of the Emergency class. This F-score is often used to illustrate the efficacy of SPMR in emergency instances. It is the average of the F-scores produced from ten runs of the experiment using test data, which is the F-score (avg.). Only data from the Emergency class is used to calculate an F-score (Emergency).

1) ACCURACY OF PREDICTION

$$Accuracy = \frac{True\ results}{Total\ Cases} = \frac{TP + TN}{TP + TN + FP + FN}$$

False Positive, False Negative, and True Positive are all abbreviations for the same thing: "True Positive." A comparison of the accuracy of the predictions is provided (see Fig. 6).

2) REPRESENTATION F-SCORE

The model's precision on a dataset can be evaluated using the F-score, often referred to as the F1-score. Binary classification systems, which categorise instances into 'positive' or 'negative,' are evaluated using this method.

It is defined as the harmonic mean of the model's accuracy and recall, which is a means of combining precision and recall.

Information retrieval systems like search engines and a variety of machine learning models, particularly those involved in natural language processing, are often evaluated using the F-score.

Figures numbers 7 and 8 represent the mean F-score and the F-score for emergency cases, respectively.

$$F-score = \frac{2 * (Recall * Precision)}{(Recall + Precision)}$$

3) REPRESENTATION OF PRECISION

$$Precision = \frac{TP}{TP + FP}$$

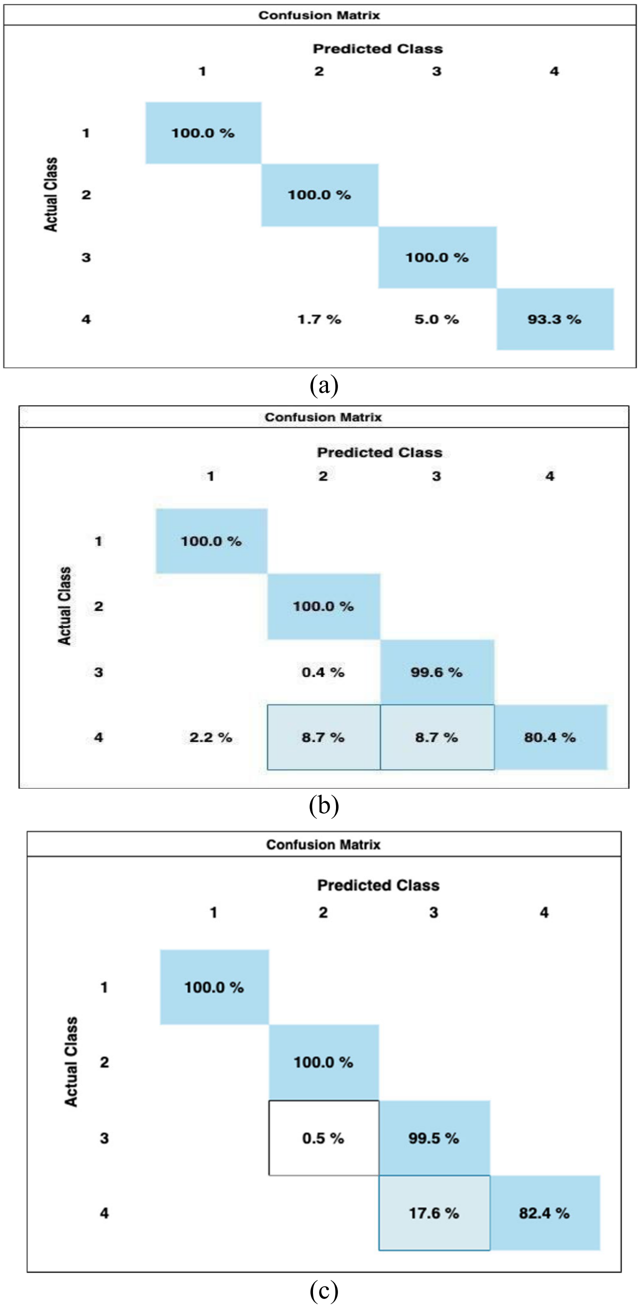

FIGURE 5. **(a) Confusion matrix generated by Cloud Predictive Modeling (CPM) for an individual with hypertension (P1), (b) Confusion matrix for hypotensive patient (P2) and (c) Confusion matrix for a normal patient (P1) (P3).**

4) SENSITIVITY/ RECALL

The term "sensitivity" originates from the field of statistics to describe how well a binary classification performs, but the term "recall" is more closely associated with the field of information engineering.

$$Sensitivity = \frac{TP}{TP + FN}$$

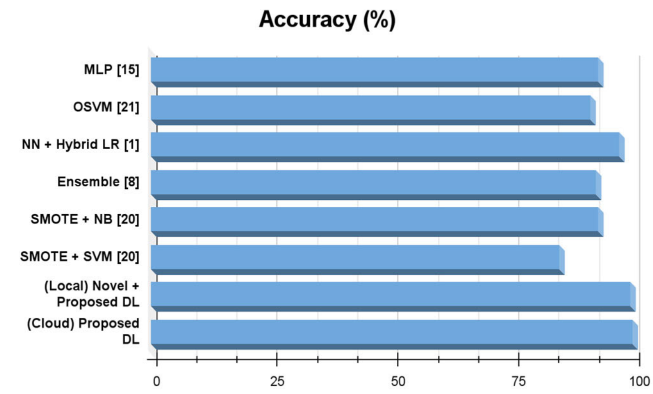

FIGURE 6. **Predictive accuracy is compared against current research.**

5) COMPARISON, DISCUSSION AND RESULTS

The integration of Deep Learning (DL) with a novel Categorical Cross Entropy (CCE) optimization in SPMR demonstrates remarkable performance and efficient convergence. The proposed SPMR exhibits significantly higher accuracy across all patient groups compared to existing studies. Sensitivity ranges from 0.79 to 0.93 when compared to alternative models. Notably, SPMR's Local Predictive Model (LPM) outperforms in hypertensive individuals, achieving a notably higher F-score (emergency), while the Cloud Predictive Model (CPM) excels slightly in hypotensive and normotensive patients. Despite data imbalances, all classifiers achieve an average F-score surpassing 0.90, showcasing the effectiveness of SPMR in forecasting urgent situations, notifications, cautionary signals, and standard occurrences.

During the validation phase of our research on "Smart Patient Monitoring and Recommendation (SPMR) using Cloud Analytics and Deep Learning," certain limitations and constraints were encountered. One notable constraint involved the availability of long-term monitoring data for patients with chronic diseases, particularly high blood pressure, using IoT sensors. The scarcity of such data posed challenges in creating a realistic and diverse dataset for training and testing the SPMR framework. Additionally, the imbalance in the dataset categories, especially concerning emergency and alert incidents, influenced the performance metrics. These limitations highlight the need for further exploration and data acquisition strategies to enhance the robustness and generalizability of the proposed framework in real-world healthcare scenarios. The validation phase served as a valuable opportunity to identify these constraints, paving the way for future research improvements and advancements in smart patient monitoring systems.

B. CLOUD ANALYTICS INFRASTRUCTURE

This section unveils the essential components and elements that constitute the Cloud Analytics Infrastructure supporting the "Smart Patient Monitoring and Recommendation

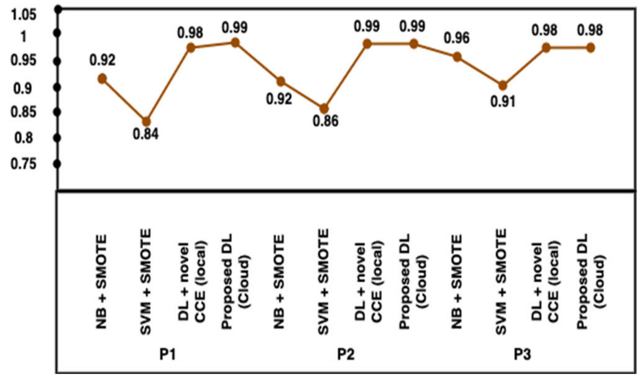

FIGURE 7. P1, P2, and P3, the average F-score (Average) is compared to work done in the last one year.

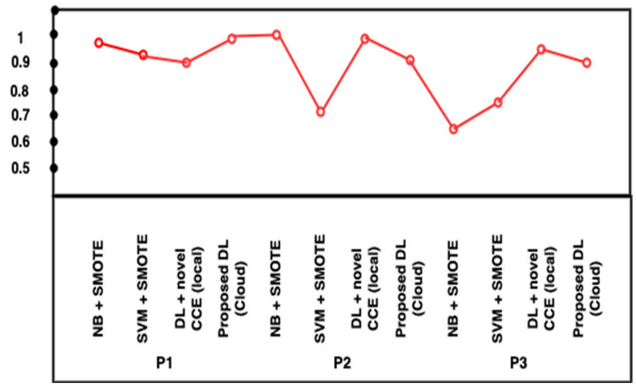

FIGURE 8. Analyzed in comparison to more current work over a period of one year, F-scores for P1, P2, and P3.

(SPMR) using Cloud Analytics and Deep Learning" framework in healthcare innovation. Leveraging the power of Deep Learning (DL) and cloud-based analytics, SPMR ensures continuous monitoring and predictive insights into a patient's authentic health status. The incorporation of Categorical Cross Entropy (CCE) Optimization within the DL component emphasizes the adaptability of the framework to real-world health conditions. Notably, SPMR's ability to provide real-time preventive measures persists even without Internet or cloud connectivity, streamlining operational processes. Through comparative analysis against similar models, the efficacy of the proposed SPMR model becomes evident, showcasing heightened accuracy and significant improvements in F-scores. This section provides a transparent and insightful overview of the Cloud Analytics Infrastructure of SPMR, elucidating the necessary platforms and technologies, thereby contributing to the evolution of healthcare monitoring systems.

VI. FUTURE RESEARCH RESULTS AND CONCLUSIONS

The SPMR system keeps tabs on chronic illness sufferers who are located far away, such as hypertension and diabetes, in real time. This framework's local and cloud implementations are equally effective at forecasting crucial events such as power outages and natural disasters.

Using a new CCE optimization approach in combination with a novel DL technique, we were able to decrease the discrepancy between the predicted and actual label error rate. Uniqueness increases the likelihood that the DL algorithm will reach efficient convergence. Our work is ground-breaking since we identify massive datasets using a cloud-based prediction algorithm hosted on GCP.

To sum up, the study successfully met its main goals, and here are the main discoveries and contributions:

- Efficient Remote Monitoring: The SPMR system demonstrated real-time monitoring of chronic illness sufferers, particularly those at a distance, such as individuals with hypertension and diabetes.
- Equal Effectiveness of Local and Cloud Implementations: Both local and cloud implementations of the SPMR framework proved equally effective in forecasting crucial events, including power outages and natural disasters.
- Enhanced Prediction Accuracy with CCE Optimization: The implementation of a new Categorical Cross Entropy (CCE) optimization approach, coupled with a novel Deep Learning (DL) technique, significantly reduced the discrepancy between predicted and actual label error rates. This uniqueness enhances the likelihood of efficient DL algorithm convergence.
- Groundbreaking Cloud-Based Prediction Algorithm: The work breaks new ground by identifying massive datasets through a cloud-based prediction algorithm hosted on Google Cloud Platform (GCP). This innovation contributes to the robustness and scalability of the proposed framework.

These findings collectively highlight the effectiveness and innovation of the "Smart Patient Monitoring and Recommendation (SPMR)" framework, paving the way for advancements in remote patient monitoring systems.

SPMR has the following advantages over other frameworks:

- Offline learning is resilient due to its high performance, and an expert may provide ideas that take context into consideration.
- Utilization of deep learning algorithms is required (cognitive techniques). It reduces the amount of time and effort needed to do parallel processing.
- In contrast to other frameworks, this one instals the cloud-based learner across the local network.
- Even when the Internet goes down and cloud services are unavailable to you, you'll still be able to access your data.
- Capable of managing large datasets that are inconsistent and poorly structured.
- A common source of an overfitting issue is the omission of sampling strategies.
- The health status of patients may be collected, kept, monitored, categorized, and forecasted.
- Big data analysis may be accommodated by deep learning via the cloud computing platform such that it has

high performance in terms of prediction accuracy, precision and categorical accuracy.
- Constant monitoring of a patient from a distance increases healthcare quality.
- Testing on a legitimate cloud computing platform, for example, it may make use of cutting-edge technologies like AI, IoT, and cloud computing.

Using DL packages like as Scikit-learn, TensorFlow, and Keras, our research team has shown that deep neural networks may be deployed rapidly and with little effort on local computers. In the future, the framework proposed might be used to develop various deep learning algorithms. Other chronic conditions, such as cancer, will be tested utilizing the context-aware framework that has been presented. According to [54], [55], [56], [57], [58], and [59], the suggested framework will be evaluated on a variety of quality of service (QoS), energy use [60], [61], [62], [63], and social network service (SNS) in the cloud (Cloud) criteria.

VII. FUTURE WORK

Our ongoing research efforts will focus on further refining the SPMR framework and extending its applicability to diverse healthcare scenarios. We aim to explore the development of additional deep learning algorithms within the proposed framework, with a specific emphasis on addressing various chronic conditions, such as cancer. Evaluation criteria will expand to include comprehensive assessments of quality of service (QoS), energy efficiency, and social network service (SNS) in the cloud. Additionally, we will investigate the integration of emerging technologies and frameworks to enhance the SPMR system's capabilities, ensuring its relevance and effectiveness in the evolving landscape of healthcare technology.

Potential Improvements and Future Research Avenues:

- Enhanced Offline Learning: Explore avenues to further enhance the resilience of offline learning by incorporating advanced context-awareness and feedback mechanisms from healthcare experts.
- Addressing Overfitting Issues: Develop and implement advanced sampling strategies to address overfitting issues, ensuring more accurate and reliable predictions with large and inconsistent datasets.
- Expansion to Other Chronic Conditions: Extend the framework to accommodate and monitor additional chronic conditions beyond hypertension and diabetes, such as cancer, utilizing the context-aware approach presented.
- Evaluation on Diverse Criteria: Conduct comprehensive evaluations of the proposed framework on various quality of service (QoS), energy consumption, and social network service (SNS) criteria in the cloud environment, as suggested by [54], [55], [56], [57], [58], and [59].
- Integration of Emerging Technologies: Explore the integration of emerging technologies like Artificial Intelligence (AI), Internet of Things (IoT), and advanced cloud computing technologies to further enhance the capabilities and features of the SPMR framework.
- Efficiency and Scalability: Work towards improving the efficiency and scalability of the deep neural networks, enabling rapid and effortless deployment on local computers while maintaining high performance.
- User-Friendly Framework Development: Focus on developing a user-friendly framework that facilitates the rapid development and testing of various deep learning algorithms, promoting accessibility and adoption by a broader audience in the healthcare domain.

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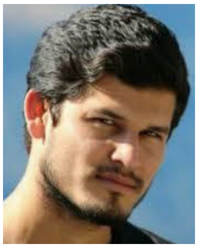

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