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A Review on Machine Learning and Deep Learning Techniques for Medical Internet of Things (m-IoT)

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Abstract:

The mobile health care over Internet of Things (IoT) offers flexibility and fast clinical diagnosis irrespective of distance and viewing displays. The delivery, management, and oversight of medical services have undergone a radical transformation as a result of the integration of Machine Learning (ML) and Deep Learning (DL) techniques in the mobile healthcare domain. To achieve better Quality of Service (QoS), the present networks needs more lime light of research in terms of streaming the medical videos without sacrificing the medical quality of experience (mQoE).Researchers have addressed various issues and proposed numerous solutions in terms of machine learning for IoT in mobile healthcare. The article provides a thorough analysis of contemporary machine learning (ML)/Deep Learning (DL) concepts, with a focus on mobile healthcare domain. It mainly focus on recent developments in health care domain and also opens research issues that need to be addressed in the future A wide range of topics, including the diagnosis and classification of diseases, customised therapy suggestions, remote patient surveillance and their health behaviour analysis have been covered. A comprehensive review has been conducted on IoT in healthcare, Big medical data in IoT, ML and DL models and ML challenges in IoT healthcare. This survey of IoT based medical data transmission is focused on recognising an accurate prediction model. The simulation results and comparison analysis of various ML/DL algorithms have been presented. The medical image classification have been evaluated based on several metrics including prediction accuracy, specificity and sensitivity. These metrics have been compared and tabulated for various learning algorithms like Artificial Neural Networks (ANN),Naïve Bayes Classifier (NB), Reinforcement Learning (RF),Support Vector machine (SVM),Convolutional Neural Networks (CNN). Finally, a frame work for a secured multipath medical video transmission using the hybrid version of the above discussed algorithms has also been suggested.

Keywords: Mobile healthcare, Machine learning, Deep learning, Big data, Internet of Things.

1. Introduction

Currently, the number of devices with internet access is growing in health care IoT networks. The Internet of Medical Things (IoMT) devices in use, have already reached nearly 30 billion and the number is increasing faster. Mobile health care over IoT networks provides the ability to monitor

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patients in real-time, offering a more sophisticated and efficient way to gather medical data, and tracking staff and patient activity. They offer flexibility and provision of viewing the clinical and diagnostic information including the ultrasound videos irrespective of the distance and viewing displays. But achieving these advantages in the present networks needs more lime light of research in terms of streaming the medical videos without sacrificing the medical quality of experience (mQoE). Each of the stages may have an impact on the level of experience since video streams are more vulnerable to flaws in the capture, pre-processing, transmission, and post-processing processes. In addition to the limitations already discussed, the responsibility of the network and the qualities of the material both affect perceived quality of experience.Fig.1 shows the role of IoT in mobile health care.

Figure.1 Role of IoT in Health care

The demand for video traffic in increasing over IoT networks [2] . However, wireless link capacity for IoT cannot meet its traffic demand due to the interference problem that still considered to be a real challenge in IoT networks. Consequently, it results in some major problems such as poor quality in video streaming, service interruption and even fault diagnosis. So intelligent streaming is required to transfer medical data over different networks.Fig.2 depicts the gathering of data from various IoT devices into the cloud.

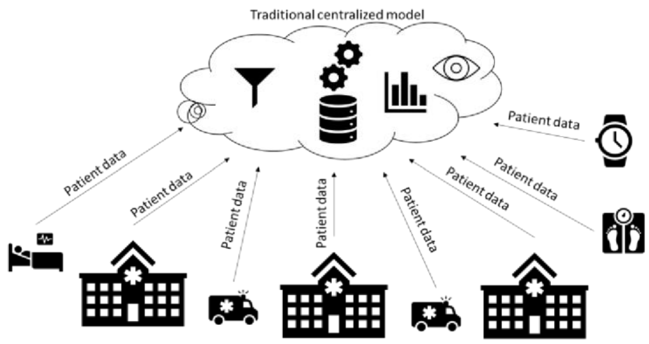

Figure.2 Data gathered from several hospitals in to the cloud

The IoT technology also has several challenges in terms of safety and security, interoperability, big data analytics, energy efficiency and network Quality of Service (QoS) . The big data generated from IoT devices is considered a major issue since they consumes a huge data storage. But the huge collection of health data is used for the analysis and for an accurate decision making. This big data analytics in IoT applications has been developed by various scholars using several models [4-6].

To improve the QoS and mQoE, various Machine Learning (ML) and Deep Learning (DL) based intelligent techniques are implemented. These methodologies comprise of two stages including training and testing the model for a prediction. The training and testing of intelligent methods for big data prediction, involves pre-processing of the dataset, Feature Extraction and Classification to improve the QoS and mQoE. Due to the huge big data training and learning strategies of ML and DL models, the medical video data are processed with a higher quality[3].

The rest of the work is structured as: the survey on the fundamental of IoT networks ,IoT medical Big data and the popular ML/DL algorithms is discussed in section 2. Section 3 presents the evaluation metrics followed by the comparative study of various algorithms. Finally, the discussion is concluded in section 4 correspondingly.

2.Related works

In the future, IoT will be incorporated into almost every area of healthcare and will update the current healthcare system and offer faster and better services. The current section presents the most recent research on IoT and bigdata based mobile health systems with the goal of seamlessly connecting patients and medical experts across diverse healthcare systems. With the simplicity with which patients' medical information may be accessed through simultaneous announcement and checking via linked devices, medical care professionals will be better able to offer patients evidence-based medicines and repeat treatments. This survey covered the fundamentals of mobile health care over IoT and existing key methodologies for medical video transmission in IoT using machine learning and deep learning techniques. It finds the research gap in existing framework to propose the counterfeit mechanism for the fair medical data transmission. Figure 3 shows the flow of the literature reviewed.

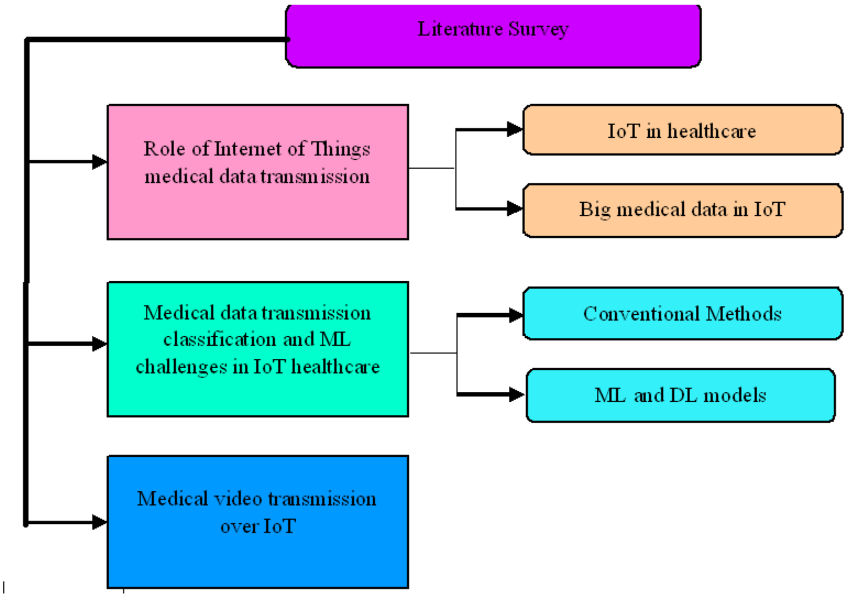

Figure 3: The literature survey flow diagram.

2.1 HEALTHCARE IoT and BIG MEDICAL DATA

The time and money used for conventional medical monitoring are adequate. A licensed clinician must frequently check on the patient in person, and it can take several days to prepare test findings. In order to ensure that everything is going according to plan with their health after being released from the hospital, recovering people might need to schedule a few sessions for the subsequent check-ups. Several problems are being explored in depth since the IoT's development. Patients' wellbeing is continually monitored via wearable and implantable technology, regardless of the time of day or the person's place. These devices possess centralized artificial intelligence (AI) models that grant them the capability to not only detect the future but also predict it.

The patient and the relevant physician can receive prompt notifications. The field of study related to this is commonly known as "ubiquitous health" (uHealth), "eHealth," and "mobile health" (mHealth). Its primary objectives encompass reducing healthcare expenditures, enhancing patient contentment, alleviating the strain on hospitals, particularly in emergency scenarios, and creating transparent, precise, and promising AI models to assist doctors in disease diagnosis, prevention, and personalized treatment provision. [7].

In order to extract and analyze relevant information, all the medical data must be transmitted to a cloud-based data center in a simplified scenario. However, this process faces challenges such as network congestion and insufficient resources for real-time analysis of the medical data. Various solutions have been proposed to address the first issue, including removing excess data and outliers on the local device, aggregating data before transmission, and utilizing available AI models to perform basic analysis and transmit medical data only when a problem is predicted [8]. AI techniques are currently widely employed to process, comprehend, and extract knowledge from the collected medical data, as they can operate independently once their training phase is completed, eliminating the need for additional guidance.

2.2 MEDICAL DATA TRANSMISSION CLASSIFICATION

The medical data transmission classification is subdivided into 2 categories which are represented in Figure 4.

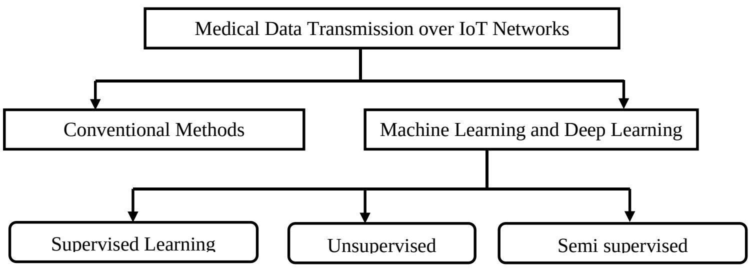

Figure 4: classification of medical data transmission over IoT Networks

2.2.1Conventional Methods for Medical Data Transmission over IoT Networks

Utilising health prediction algorithms, hospitals may move outpatients to treatment centres quickly, alleviating traffic and ensuring that more patients receive prompt care. This tackles the frequent issue of abrupt changes in the patient influx within hospitals. The requirement for high-quality healthcare services in hospitals is influenced by emergency situations, such as admissions resulting from unanticipated disasters and accidents, as well as routine clinic demands [9]. While some institutions may see lower patient volumes, clinics without real-time patient flow data frequently find it difficult to adequately manage the demand. By tying together digital and physical devices within the network, the Internet of Things (IoT) plays a significant part in establishing communication. It makes quick data collection possible by utilising sophisticated microcontrollers. It is important to remember that healthcare is the process of improving and maintaining health by identifying and preventing illnesses. Diagnostic tools including CT, MRI, PET, and SPECT can be used to examine anomalies or ruptures that happen below the skin's margin. The monitoring of specific abnormal disorders, such as epilepsy and heart attacks, is also possible [10]. Contemporary health systems are under pressure due to the population boom and the irregular growth of serious diseases. There is a strong requirement for all types of medical resources, such as doctors, surgeons, and hospital wards . Hence, there is a need to alleviate the strain on healthcare systems while maintaining the predetermined criteria and level of service quality. Despite the benefits of leveraging the Internet of Things in healthcare, both patients and medical professionals express concerns regarding data security.

Research has proposed the utilization of IoT and Machine Learning (ML) for monitoring patients with medical conditions while ensuring a minimum level of data security to safeguard data integrity. With the integration of IoT, the healthcare sector has entered a new era where healthcare professionals can actively engage in communication with patients. The Internet of Things leverages machine learning to assess the need for emergency medical care and develop plans to address such situations during specific seasons. Crowded reception areas are a common issue in many outpatient clinics [13]. Hospital visitors present with a variety of ailments, some of which require prompt medical attention. However, when those in need of emergency care are forced to wait in lengthy queues, the problem only exacerbates.Hospital staff shortages in developing nations make the issue worse. Owing to medical overpopulation, numerous people frequently leave without being treated.

[13] The implementation of WMSs and their advancements were thoroughly examined by the writers, who also evaluated how they performed in comparison to other platforms. The benefits of using these gadgets to monitor the health of individuals with illnesses including cardiopulmonary arrest and vascular dementia were explored by the authors. A fuzzy based monitoring system that suits for Wireless Sensor Network (WSN) was proposed by Miotto et al [14]. In order to establish a Body Sensor Network (BSN) that routinely detects abnormalities in patients' health, researchers specifically combined wireless sensor network with Micro-Electromechanical Systems (MEMS).

Notably, the authors created a system for measuring patient information utilizing tools such as a microcontroller, temperature sensor and pulse, and [12]. In order to remotely control patients' temperatures and pulses as well as to transmit the patient's data to the experts's phone, an equipment for base station was also added to the suggested system. In case of an emergency, the service has the capability to send SMS notifications to both the patient's family and medical professionals [11]. Consequently, patients can utilize this method to receive prescriptions from doctors working in distant centralized institutions.

The healthcare sector can now monitor the vital signs of patients with chronic illnesses thanks to the Internet of Things [19]. By utilizing various methodologies, this framework assesses the patients' well-being based on the collected information. IoT sensors are placed on the patient's body to monitor their activities, track their movements, and predict their health status. For example, a sensor module can closely monitor diabetic patients to anticipate patterns of illness and identify any unexpected conditions.Through the health prediction system, patients can get recommendations for different hospitals where they could get treatment. Those who want to stay in the same facility but don't want to go to any other facilities can, but they might have to wait in lines that could be long.

Rajkomar et al. [20] created a Zigbee Technology-hinged and BSN clinical monitoring platform in order to proactively study ill persons utilising medical sensor data. Authors specifically employed protocols including the Zigbee IEEE 802.15.4 protocol, spirometer data, heart rate, temperature signals, and EKG to assess people's wellbeing[21]. Visual appliances such as desktop laptops or cellphones receive the data via radio waves in order to display it. The suggested platform may therefore monitor patient traits like glucose, temperature, respiration, ECG, EEG, and blood pressure while transmitting the data through Wi-Fi or GPRS to a database.

Zigbee allows visibility on emergency equipments and the mobile phones of doctors' and family members' by receiving sensor data and transmitting it to a different network [12]. IoT and machine learning integration thus simplify the management of patient wellbeing by improving the relationship between patients and their doctors. For the supervision and monitoring of patients, the Internet of

Things (IoT) offers hardware- and software-based sensor networks. The latter has gadgets like a Raspberry Pi board, temperature and blood pressure sensors, and heart rate monitors. The software mechanism gathers sensor data, uploads it to the cloud, and then analyses it to find health anomalies [23]. Anomalies, however, usually develop when unidentified processes take place in unidentified body sections.

For instance, during a brain seizure, it is typical to observe an increase in pulse rate. Machine learning techniques are employed to establish a connection between the heart rate sensor and Raspberry Pi boards, enabling the display of abnormal results on LCD or serial monitors. Given the large volume of data points, cloud computing is utilized to store the data and enhance data analysis [25]. Various open-source cloud computing platforms are compatible with Raspbian Jessi and Raspberry Pi hardware . These devices utilize machine learning algorithms to analyze the recorded data and identify any deviations . In the context of the Internet of Things, machine learning techniques are leveraged to detect anomalies resulting from unrecognized activity in diverse biological components (IoT).

2.2.2 Machine Learning and Deep Learning based Medical Data Transmission Over IoT Networks

It is worth highlighting that machine learning is a subset of artificial intelligence (AI). The fundamental goal of machine learning is to learn from experiences and patterns. Rather than relying solely on traditional methods that involve writing code, machine learning algorithms utilize large datasets to perform analysis and learn from the available data. With the aid of big data, IoT, and machine learning systems, it becomes possible to train a system rapidly using vast amounts of data to predict medical issues. The predictive performance of such systems improves as they are exposed to larger datasets [28]. Consequently, the integration of big data into healthcare prediction systems enhances the accuracy of machine learning techniques.

Machine learning-based methods for clinical load prediction are developed to facilitate efficient transfer of patient routing information between hospitals. These methods leverage historical data to forecast patient loads in clinics, ensuring adequate planning. IoT devices integrated with machine learning algorithms are used to train classifiers capable of recognizing specific health events, such as falls in elderly individuals. Clustering algorithms prove effective in identifying abnormal patterns of patient behavior and alerting healthcare professionals. IoT microchips are utilized in a manner similar to modeling daily routines, enabling the tracking of patients' daily activities. This data is then utilized to detect irregularities in the routines of older individuals.

The objective of this study is to analyze the prevalent machine learning (ML) methods used for the classification and prediction of IoT data in the healthcare industry. The study compares these methods based on various characteristics to evaluate their performance. By conducting a detailed examination of the existing literature, the paper highlights the strengths and weaknesses of each technique and identifies any gaps that exist. The aim is to identify the most suitable algorithms for building an effective prediction model. According to the findings of this study, the K-Nearest Neighbour (KNN) technique is commonly employed for prediction and classification tasks. However, it is important to note that real-time prediction using KNN may require a certain amount of time. Because of this, several researchers have suggested that merging Recurrent Neural Networks (RNN) with Long Short-Term Memory Neural Networks (LSTM) may enhance prediction performance. This study answers the following query: How can machine-based algorithms and IoT data be integrated to create a more accurate healthcare prediction system?

ML models and classification, the most popular ML algorithms used for a variety of prediction applications, ML algorithm applications, and the usage of IoT and ML in the healthcare field were all explored in the sections that followed.

2.3 ML algorithms and classification

Machine learning is a phenomenon within the realm of AI (ML) that enables a system to automatically process and comprehend various inputs through experience . The creation of an effective ML model involves training and testing. In the labor-intensive training phase, the system is provided with labeled or unlabeled inputs to learn from. These inputs are stored in the feature space to serve as a reference for future predictions. During testing, the system is required to predict the correct outcome based on an unlabeled input.

Machine learning techniques are increasingly being integrated into healthcare applications, including clinical decision support systems, to enhance their functionality. Support Vector Machines (SVM) and artificial neural networks are examples of machine learning models commonly used in healthcare applications. These models are utilized in various applications, such as accurate classification of different types of cancer. By analyzing data collected from sensor devices and other sources, these algorithms are able to identify a patient's clinical conditions and behavioral patterns. This integration of machine learning enables healthcare systems to provide more comprehensive and personalized services.

These algorithms, for instance, can recognize abnormalities in a patient's behaviour, variances in daily activities, changes in eating, drinking, sleeping, and digestive patterns, as well as alterations in mobility. These behavioral patterns identified by the algorithms can be used by clinical decision support systems and monitoring devices to prescribe modifications to patients' habits and lifestyles as well as specialized medicines and healthcare regimens. This makes it possible for medical professionals to design a treatment strategy that guarantees patients follow suggested lifestyle modifications. Unsupervised learning, semi-supervised learning, and supervised learning are the three main model types covered by machine learning technology.

The common algorithms for each ML type are depicted in Figure 5. The most common machine learning (ML) techniques used for prediction and classification are introduced in this section. These techniques include Gradient Boosted Regression Trees, Random Forest, Nave Bayes, Decision Trees, Support Vector Machines (SVM), Neural Networks, and K-Nearest Neighbor in Supervised Learning [31].

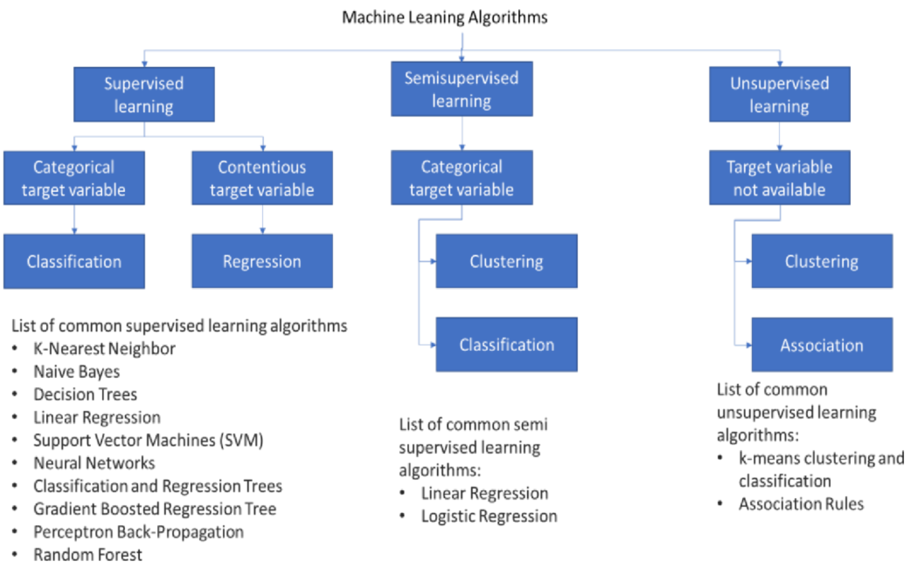

Figure 5: Machine learning algorithms' classification

For an accurate prediction, the classification task is most important. An accurate classification is done by a ML/DL method that is widely used for various applications. A few popular methods are defined shortly in the following. NB model is based on principle of bayes that is assumed independently among predicted values. This is a best classifier which has a specific feature class that is not relevant to available features classes in present.KNN method is defined as the similarity relation between current information and available information is determined. The predicted new information is marked as most required data category.SVM is based ML model that is mostly used to solve non-linear and linear issues. This model mostly handled a classification, regression and outliers' prediction. It attained a maximum accuracy in problem solving and also provide a maximum dimensional space with an efficiency.MSVM is upgraded method of SVM that handled a multiclass classification. The MSVM processed multiple classification problems to multiple binary classification problems and then performed a SVM model.

NN model is inspired and developed by an activity of human brain. There are three important layers such as input, hidden and an output layer are presented in it. The input fetched the data, the computations are done by hidden and output value are provided using an output layer.CNN model is a significant ML/DL method which is followed by a Neural Network. The CNN model is used for weight and bias learning for various objects. This method discriminated a one object from another.

DT model is defined as a graphical representation that is easy to simply the computation and made a decision even for a complex case. Each DT method is used for features classification to categorise a labels or classes.RF model is used to rectify an issue in regression and classification by integrating a several DT classifiers. These classifiers are combined and computed to achieve a good decision making in complex issues.

LSTM model is related to a RNN that is used to process a long-term dependency. It is a sequential network which can be processed a gradient vanishing issue occurred in RNN and achieve a highly learned data for prediction.

Table 1 provides a summary of all the ML algorithms that have been examined.

Table 1 Summary of the reviewed ML algorithms

Name of the algorithm	**Type of learning**	**Utilization purpose**	**Pros**	**cons**
K-Nearest Neighbor (K-NN)	Supervised	Classification, Regression	Using a nonparametric method. Simple to comprehend. easy to put into action Lacks a need for formal training. Simple updating of its set of labeled observations will allow it to be easily modified.	Calculating the similarity between the datasets is time-consuming. Unbalanced datasets cause the performance to suffer. The hyper parameter selection affects performance (K value). This framework must employ homogeneous characteristics since it risks losing the information.
Naïve Bayes (NB)	Supervised	Probabilistic classification	scanning of the data by examining each characteristic separately. The correctness of the assumptions is	simply calculates the variances for the parameters in each class.

			improved by simple per-class data collection from each feature.	
Decision Trees (DTs)	Supervised	Prediction, Classification	Simple to implement. Can handle continuous and categorical qualities. minimal to no data preparation.	sensitive to training dataset noise and an unbalanced dataset. costly and using more memory.To prevent bias and variation, the depth of the node must be carefully chosen.
Random Forest	Supervised	Classification, Regression	Less correlation between the decision trees as a whole. enhances the DT's efficiency.	This methodology won't function with highly dimensional, sparse data..
Gradient Boosted Decision Trees	Supervised	Classification, Regression	iteratively increases the performance in prediction.	Requires precise parameter adjustment and may be time-consuming to train. Does not do well with less dense and high-dimensional data.
Support Vector Machine (SVM)	Supervised	Binary classification, Nonlinear classification	In high-dimensional space, more efficient. The true power of SVM lies in the kernel trick.	It is difficult to choose the optimum hyperplane and kernel trick.

2.4 MACHINE LEARNING based MEDICAL VIDEO TRANSMISSION OVER IoT

In their study, Muhammad Ismail et al. [1] employed multihoming management to transmit data through various remote access channels. They proposed an energy and resource-aware video transmission framework that addresses the power limitations of mobile terminals (MTs) and the quality-of-service (QoS) requirements of video streaming applications. By leveraging the opportunities offered by a heterogeneous remote access medium, the framework aims to maintain video quality without degradation. To achieve this, the MT intelligently distributes packets within the constraints of battery power and prioritizes important packets across different radio interfaces. This approach ensures a seamless video streaming experience. The authors describe their work as addressing an NP-hard problem called MINLP, which involves a combination of learning techniques such as supervised learning and guided learning.

Cutting plane technique is used to tackle the issue in a piecewise linearization method, which lowers the associated MINLP complexity to a set of MIPs. The work's conclusion used a two-arrangement enhancement problem for practical execution in MTs to anticipate the video transmission system. Numerical findings show that the suggested system executes very nearly to the carefully defined problem structure. The application of artificial intelligence (AI), information analysis, and natural-language processing (NLP) systems for improving remote system activity productivity is comprehensively examined in this paper by Tadilo Endeshaw Bogale et al. [26]. This study focuses on the usage of these systems for board of cutting-edge remote computers, professional information procurement, information disclosure, planned arranging, and activity.Additionally, a brief contextual analysis employing this system's AI techniques has been provided.

By employing consumer calculation and current Deep Neural Network advancements, Hyunho Yeo et al. [27] offer a new structure for offering high-quality video that is less dependent (DNNs). We can improve video quality while maintaining the current transfer speed by using DNNs. A workable structure is put out in order to strengthen the concept and address a few issues including client heterogeneity, cooperation with bitrate adjustment, and DNN mobility. By improving average QoE by 43.08% on average while utilising a similar budget for medical data transmission or by reducing transfer speed by 17.13% while keeping a comparable level of client QoE.

Mukhtar et al. [28] presented an adaptive hybrid automatic repeat request (HARQ) method for unicast remote video communication. This method involves the collector dynamically controlling the HARQ input messages based on factors such as the playback cutoff time, video content, and error location. A delayed model is employed to calculate the adjustment, determining the time required for a video frame to travel from point A to point B. The playback buffer occupancy and the significance of video packets are adjusted accordingly to ensure consistent playback. It is crucial to avoid incorrect decoding of video frames due to incomplete packet reception.

The performance of the adaptive HARQ approach is evaluated in the presence and absence of subpacket discontinuity. The results demonstrate that subpacket-based HARQ outperforms bundle-based HARQ in terms of delay and video playback consistency. The adjustment computation significantly improves the delayed performance of both HARQ systems by eliminating buffer starvation without compromising spatial quality.

3. ANALYSIS OF VARIOUS ML/DL ALGORITHMS

3.1 PERFORMANCE METRICS

The medical image classification can be evaluated based on the several metrics including accuracy, specificity and sensitivity . These performance metrics are computed mathematically based on the following equations.

$$\text{sensitivity} = \frac{\text{True}_{\text{Pos}}}{\text{True}_{\text{Pos}} + \text{False}_{\text{Neg}}}$$

$$\text{specificity} = \frac{\text{True}_{\text{Neg}}}{\text{True}_{\text{Neg}} + \text{False}_{\text{Pos}}}$$

$$\text{Accuracy} = \frac{\text{True}_{\text{Pos}} + \text{True}_{\text{Neg}}}{\text{True}_{\text{Neg}} + \text{True}_{\text{Pos}} + \text{False}_{\text{Pos}} + \text{False}_{\text{Neg}}}$$

Where True_{Pos} represents the true positive which is an accurate data, True_{Neg} represents as True Negative that is dangerous and predicated as negative, $\text{False}_{\text{Pos}}$represents the False Positive that is harmful but positively predicated and $\text{False}_{\text{Neg}}$indicates the False Negative which is positive in result but predicated as negative.

3.1 Simulation results for evaluation of various Algorithms

The prediction accuracy ,Sensitivity and Specificity for various learning algorithms have been evaluated ,compared and tabulated.

Table 2 Comparative Analysis for various learning algorithms

Sl.No	Type of Algorithms	Prediction Accuracy(%)	Sensitivity (%)	Selectivity(%)
01	ANN	93	90%	91.5%
02	NB	89	89.0%	88.5%
03	RF	94	93%	93.5%
04	SVM	94	94%	95.5%
05	CNN	92	96%	95.5%
06	RNN	97	96.5%	96%

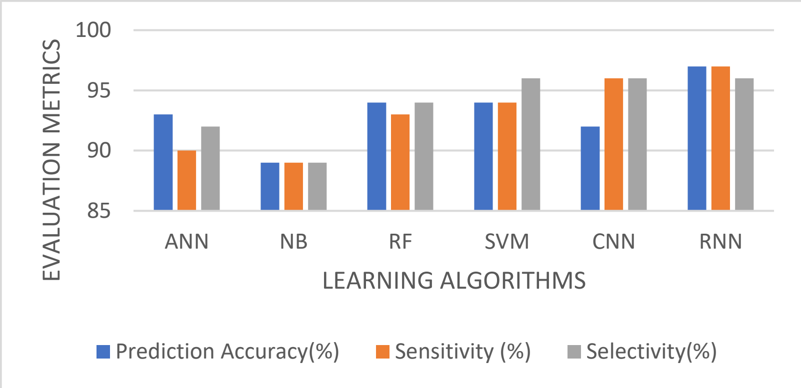

Figure 6: Prediction accuracy of various algorithms

Fig.6 shows the Prediction accuracy,Sensitivity and Specificity of various algorithms.The prediction accuracy of artificial neural network is found to be 91.5%.The naïve bayes classifier gives an accuracy of 88.5%.The reinforced learning strategy provides an accuracy of 93.5%.Both the support vector machine and the conventional neural network ,predicts with an accuracy of 95.5%.The recurrent neural network gives an prediction accuracy of 96%.

The % sensitivity of artificial neural network is found to be 90%.The sensitivity % for a naïve bayes classifier is 89%.The reinforced learning strategy and support vector machine provide a sensitivity of 93% and 94% respectively.The conventional neural network ,have a sensitivity of 96% and that of a recurrent neural network is 97%.

The % selectivity of artificial neural network is found to be 91.5%.The naïve bayes classifier gives an accuracy of 88.5%.The reinforced learning strategy provides an accuracy of 93.5%.Both the support vector machine and the conventional neural network ,predicts with an accuracy of 95.5%.The recurrent neural network gives an prediction accuracy of 96%.

4.CONCLUSION

In this work, the survey of IoT based big medical data transmission is focused for recognising an accurate prediction model. This review sheds light on the current state, future trends, and revolutionary impact of ML and DL in the mobile healthcare domain, offering useful insights for researchers and healthcare professionals .This paper studied the fundamental of IoT in the medical field and also the basic procedure of ML/DL methods.It also focussed on various ML/DL Algorithms and discussed with respect to various works.Then ,simulation results and comparison analysis of various algorithms such as ANN,NB,RF,SVM,CNN and with respect to evaluation metrics such as prediction accuracy,sensitivity and selectivity have been discussed. This literature review leads to the conclusion, that the integration of ML and DL in mobile healthcare is a paradigm shift that has enormous potential to improve patient care, medical diagnosis, and treatment. However, it demands dealing with the underlying difficulties and grasping chances for development.Future directions for this study includes the development of a frame work for a secured multipath medical video transmission using the updated version of above discussed algorithm for which the performance not only depends on the network QoS but also on the mQoE of the end user.

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