International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
***Article Received:** 15 February 2023 **Revised:** 02 March 2023 **Accepted:** 30 April 2023*

A Novel Big Data Approach Using Fuzzy Rule Based Multilayer Perceptrons

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ABSTRACT: They are faced with immense quantities and high velocity of data with complicated structures in the big data era. Social networks, sensors, online and offline transactions, and our daily lives can all produce data. When big data is processed correctly, it can lead to relevant, helpful and useful decisions being made in a number of areas, including government, business, management, and medicine and healthcare. Large amounts of data on healthcare have the ability to significantly enhance patient outcomes, predict epidemics, provide insightful information, prevent diseases that may be prevented, reduce the cost of healthcare delivery, and generally increase life. Big data is made up of patient data that is gathered for remote healthcare applications that differs in terms of volume, velocity, variety, veracity, and value. Healthcare data classification presents a number of challenges for big data since it gathers huge quantities of data. Processing a heterogeneous collection of this size requires a specialized approach, making it one of the most difficult challenges. The paper presents a novel big data approach using fuzzy rule-based multilayer perceptrons to address these problems. Big data offers the ability to accumulate, analyze, manage, and integrate large amounts of disparate, structured, and unstructured information generated by the healthcare systems of currently. A FRCNN (Fuzzy Region based Convolutional Neural Network) classifier is designed to perform normal and disease classification. Accuracy, precision, recall, and F1-score are only some of the performance criteria used to evaluate this model.

Keywords: Big Data Analytics, Healthcare Data, Security, Privacy, Fuzzy and Multilayer Perceptron.

I. INTRODUCTION

The dire need for an effective healthcare system has increased due to an increasing aging population and the increase in healthcare costs.

The global healthcare industry has developed to change. In fact, the clinical, operational, and financial models as well as the world of economy at large are undergoing a profound and major transformation due to the digitization of health and patient data [1]. Numerous factors are contributing to this change, such as aging populations and changing lifestyles, an increasing number of mobile devices and software applications, novel treatments, a focus on the importance and quality of care, and the application of evidence-based medicine in place of subjective clinical decisions. When combined, these variables offer a number of chances to enhance clinical decision-making, monitor adverse events, carry out disease surveillance, improve treatment for diseases affecting multiple organ systems, and improve healthcare administration, management, and policy-making [2].

The burden of disease, overpopulation, and limited financial resources have placed huge pressure on healthcare systems worldwide. The healthcare paradigm is changing in the current technological age from a traditional, one-size-fits-all approach to one that emphasizes personalized, individual care [3]. Furthermore, there are variations in the quantity and type of healthcare data. Healthcare personnel handle test results, imaging data, and other digital and analog data, such as ECG and MRI tests, in addition to the patient's medical history, physical examination, and other specific information [4]. Every day, huge amounts of data are produced by the progress of medical technology and the field of medicine. High-dimensional, variable-rich data is collected by these technologies, which include magnetic resonance imaging (MRI) and computed tomography (CT). As a result, the dimensionality of medical picture databases is greatly increasing. The growing number of medical databases

makes it challenging to manage the file system as the volume of data increases. As a result, managing medical data becomes an essential task for healthcare providers [5].
Due to the increasing requirement for record-keeping in the context of patient care, the health sector has always produced a lot of data. Furthermore, it is difficult to obtain significant insights using traditional analytical methods due to its varied and dynamic character. Big data is therefore an important issue in the health sector due to its vast amount, diversity, and simple management. Effective support for decisions is required since human capacity to analyze this data is limited [6].

Big data analytics have to be integrated into the health sector. Big Data analytics describes the methods used to analyze, process, find and reveal interesting relationships, hidden underlying patterns, and other insights about the application context being studied [7]. When analyzing a wide range of complex data, big data analytics can provide valuable information that would not be possible without technology. It can help in early trend detection, improve healthcare quality, reduce costs, and speed up decision-making in the healthcare industry [8].

Volume, variety, and velocity are the three main components of big data. The total amount of data generated and stored is called volume. Variety has to do with the various types of data that are gathered, while velocity is the speed at which data are created, streamed, and aggregated [9].
The medical field makes substantial use of machine learning techniques for disease diagnosis and medical picture analysis. It can perform a wide range of tasks, including image segmentation, fraud detection, disease prediction, and pattern recognition. The study of big data has attracted researchers from a number of sectors, including banking, healthcare, imaging, smart cities, IoT-based smart applications, tracking, and transportation systems, among others [10]. New applications are always being developed by software developers for the health and wellbeing of patients. Government and non-government organizations use big data analytics to build infrastructure that will help doctors and managers make better decisions. [11].

However, some of the most significant issues facing the big data sector include data storage, data standards, data, and data classification. Numerous studies have attempted to integrate security and data classification into the healthcare system. Continuous data breaches that target invaluable medical records have turned healthcare institutions into their a nemesis. Healthcare companies can increase their revenue and get more respect by using an accurate and efficient information security architecture in their web-based applications [12].

Allowing a computer (machine) to learn by identifying statistical regularities in data and creating algorithms accordingly is known as machine learning (ML), a sub-domain of artificial intelligence (AI). Recent years have seen the emergence of ML-based health applications, which hold considerable promise for the field of medical diagnostics [13]. Since machine learning (ML) depends on huge databases, data processing could be outsourced out to the cloud in order to save resources and save costs. The application of fuzzy learning (FL) has been demonstrated to address a wide range of real-world problems by minimizing the uncertainties present in raw data. Examples of these problems include image processing, portfolio management, and motor control. Through automatically acquiring the fuzzy membership functions, fuzzy systems are able to generate fuzzy rules from a huge quantity of training data. The final decision for a few particular tasks is then formed by linearly combining the fuzzy logic values in a defuzzifier. Hence, in this work, A Novel Big Data Approach Using Fuzzy Rule Based Multilayer Perceptrons is presented. The remaining content is arranged as follows: In Section II, the Literature Survey is explained. The section III presents A Novel Big Data Approach Using Fuzzy Rule Based Multilayer Perceptrons. The analysis of the result is evaluated in section IV. In section V, the work is finally concluded.

II. LITERATURE SURVEY

S. -D. Bao, M. Chen and G. -Z. Yang et. al., [14] explains A Signal Scrambling Method for Secure Data Storage in Medical Applications. To provide an additional layer of protection to the application layer for various types of health information, this research proposes a technique called signal scrambling, in which health information is organized using a limited amount of data, and addresses the possible security problems related to healthcare data in Internet-based applications. While the latter is transported to the cloud for storage along with security protection, the former is kept locally. The technique is more adaptable because the small amount of data could be gathered from a small amount of medical records or even from a random number generator. To demonstrate the effectiveness and efficiency of the suggested strategy, the computational complexity and security performance have been examined from both a theoretical and experimental analysis perspective. The suggested approach can be used with any type of data requiring more security protecting in complex networks.

Tang W., Ren J., Deng K. and Zhang Y. et. al., [15] explains the fair incentives-based secure data aggregation of lightweight IoT devices for e-healthcare. A technique for aggregating health data while protecting privacy was created. It safely gathers data from many sources and ensures that patients who participate receive fair incentives. To be more exact, we use signature techniques to maintain equitable incentives for patients. In the meanwhile, we integrate noises for differentiated privacy into the health data. In addition, they integrate Shamir's secret sharing with the Boneh-Goh-Nissim cryptosystem to provide fault tolerance and data obliviousness security. Discussions on security and privacy demonstrate that our plan is able to resist differential attacks, overcome the limitations of healthcare organizations, and maintain patient incentives that are equitable. Performance reviews show that processing, communication, and storage overhead can be done efficiently.

Yang W. *et al*., [16] About: A Cancellable Finger-Vein Bio-Cryptosystem Using Smart Cards for Data Security in Mobile Healthcare. A biometric cryptography technology known as fuzzy commitment scheme (FCS) is utilized by a cancelable finger vein bio-cryptosystem to both authenticate and encrypt confidential medical data. For security reasons, the biometric data should never leave the smart card in the proposed bio-cryptosystem, which maintains both the encrypted version of healthcare data and the biometric template on a smart card. The system security is further improved by the use of cancelable biometrics. The suggested scheme's validity is demonstrated by the security analysis and results from experiments. Obtaining improved biometric features in order to improve data security, this effort needs to investigate other more stable biometrics, such as iris biometrics.

P. Gope and T. Hwang et. al., [17] explains BSN-Care, or Body Sensor Network (BSN)-Based Secure Internet of Things-Based Modern Healthcare System. An secure Internet of Things (IoT)-based medical solution that uses the BSN architecture. They build two communication methods that provide entity authentication and transmission confidentiality between the local processing unit and the backend BSN server, two smart objects, using strong crypto-primitives, in public IoT-based communication networks in order to simultaneously achieve transmission robustness and system efficiency. In order to demonstrate the viability and practicability of the suggested methods, they also use the Raspberry PI platform to develop the proposed healthcare system.

Christo M. S., P. S. G., P. C. A. M. A., and R. K. M. et. al., [18] explains the to use block chain technology to securely store medical records in an efficient manner. Block chain technology was defined as a distributed method of providing security for patient medical record access. It consists of three parts: data retrieval through block chain technology, encryption, and authentication. To resist the frequent attacks, quantum cryptography is utilized for authentication, AES is used for encryption, and SHA algorithms are utilized for data retrieval. Additionally, this proposed framework maintains the security and integrity of the healthcare system while possibly ensuring patient protection.

Jai Ganesh Udayasankaran, Hsiu-An Lee, Hsin-Hua Kung, Boonchai Kijsanayotin, Alvin B Marcelo, Louis R Chao and Chien-Yeh Hsu et. al., [19] Overview A Blockchain-Based Personal Health Record Exchange Architecture and Management Platform: Development and Usability Analysis. In this study, the PHR architecture was made up of two primary parts. The first part was the PHR management platform, which allowed individuals to verify their block information, permit PHR exchanges with doctors or other medical health care providers, upload PHRs, and read the content of their records. The SHA-256 algorithm was used to determine the PHR's hash value upon upload, and the Rivest-Shamir-Adleman encryption method was used to encrypt the data before it was uploaded to a secure database. The blockchain exchange architecture, which created a private chain based on Ethereum, was the second component. Consensus was reached through proof of authority, which transmits transactions through an identity-based consensus method. The block content, timestamp, and previous hash value were added together by a hash algorithm to determine the hash value.

MarwanMbarek , Ali Kartit, HassanOuahmane et. al., [20] explains That Machine Learning Is Improving Security in Healthcare Clouds. Secure data processing in cloud environments is the aim of an innovative technique that is based on machine learning techniques. More effective methods for classifying picture pixels are usually Fuzzy C-means clustering (FCM) and support vector machines (SVM). To further lower the danger of possible medical information disclosure, they integrate an additional layer, two sets of tests are conducted to validate the proposed

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method, and the CloudSec module is integrated into a conventional two-layered architecture. The simulation results show that Support Vector Machines (SVM) are a useful concept for data protection and image segmentation at the same time. In fact, the authors found several promising results that offer new insights on ways to advance cloud services in the healthcare industry.

Tabassum S., Islam R., Sampa M. B., Yokota F., Nakashima N. and Ahmed A. et. al., [21] explains that machine learning performance can be improved by using remote healthcare data to predict health status. To determine the follow-up date and frequency, the purpose of this study is to predict the state of the registered patients. The number of visits to follow-up might be decreased to lower the cost of health management. In a four-phase data collection process, we conducted an experiment involving 271 corporate members, tracking their health status every three months. Data on dietary habits, sociodemographics, and clinical conditions are all included in the data records. However, categorical data is not directly compatible with the majority of machine learning techniques. To handle categorical data, the authors of this research used three different encoding strategies and suggested a new encoding strategy. A comparison table is shown that shows the effectiveness of eight different supervised learning algorithms with respect to three current encoding techniques.

III. A NOVEL BIG DATA APPROACH USING FUZZY RULE BASED MULTILAYER PERCEPTRONS

In this section, A Novel Big Data Approach Using Fuzzy Rule Based Multilayer Perceptrons is presented. Figure 1 displays the Block Diagram for the method that is being provided. During the data acquisition stage, patient information such as Age, height, weight, sex, Body temperature, Blood Pressure, Blood Glucose, Pulse, EEG, ECG, Patients disease history, Lipoprotein level, Family disease history, SpO_2 consumption, Uric Acid, Blood Urea, Serum Creatininen, Cholesterol, Triglycerides, Smoking and Alcohol details are collected through Body Sensor Network, Vehicular Adhoc and Device Network.

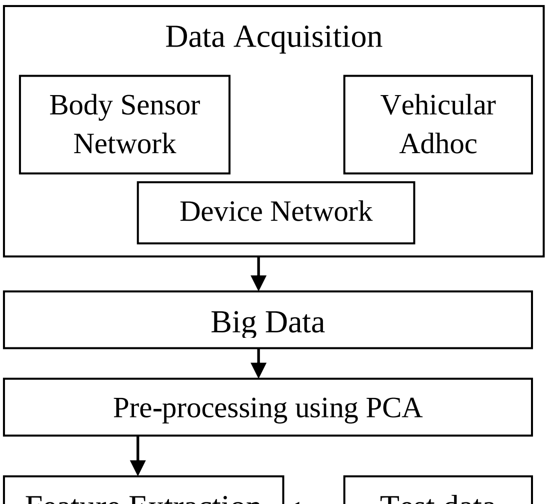

Figure 1: Block Diagram of Novel Big Data Approach

T etworks, and devices found in homes or in different hospitals provide the data. Body sensors or sensors installed in the vehicles are the two methods used to generate the data from the vehicular network. Usually, these are ambulances and hospital vans, but if the patients' own cars have the right sensors, they can also transmit data from them. The devices in these networks can either select a network head to manage the data transmission for each of these networks, or they can send data individually. Short range communication technologies including Bluetooth, ZigBee, Ultra Wide Band (UWB), devices communicate within the network using 60 GHz millimeter wave and passive radio frequency identification (RFID).

Big data helps an organization to quickly and efficiently store and handle vast amounts of data in order to get the most insightful information from it. Medical and healthcare data is considered big data due to its timeliness, complexity, and large volume. Patient-related data, such as Electronic Health Reports (EHRs), diagnostic results, prescriptions from doctors, medical imaging, pharmacy records, and research results from medical journals, are all included in health information.

Securing large health data technologies is essential from the beginning of its lifecycle from a security perspective. Thus, it's critical to collect information from reliable sources, protect patient privacy (specific patient identities in the database must not be attempted), and ensure that this stage is safe and secure. Unauthorized access must be prevented to

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all data and information systems, it is true, some complicated safety measures must be implemented.

Data can be stored in a data warehouse or as data files, depending on the type of information. Distributed big data platforms offer the ability to separate and store data on several locations. Lastly, storage optimization is handled by BDA to ensure optimal use of memory resources. Prior to processing: Missing data and additional types of noise and artifacts affect medical data and images differently. Processing techniques such as noise reduction, artifact removal, contrast adjustment, and missing data management can improve the quality of the data and images and increase processing efficiency. Pre-processing is required because healthcare data is received from multiple healthcare applications using a number of data sources, formats, and structures. Preprocessing of the medical data is done using Principal Component Analysis.

Large datasets can be reduced in size while maintaining important patterns and trends using PCA, a dimensionality reduction and machine learning technique. PCA is a technique for reducing dataset dimensionality while maintaining important information. The original variables can be changed to create a new set of uncorrelated variables known as primary components. Feature extraction is the process of transforming unprocessed data into numerical features so that the original dataset's information can be handled without losing information. It produces better results. It is the process of identifying and selecting the most important information or characteristics from the data. The preprocessed data and test data are applied to Feature extraction phase. After the feature extraction, the data is trained applied to FRCNN for classification.

Standard Multilayer Perceptron (MLP) neural networks, which are tuned for two-dimensional pattern recognition, are an early form of CNNs. For the purpose of classification, the FRCNN method makes use of both neural and fuzzy systems. The complete classification system is created by combining the data gathered using fuzzy and RCNN (Region Based Convolutional Neural Network).

It is necessary to create fuzzy rules in order to carry out fuzzy inference. Every input is rated according to the degree of membership in each fuzzy set when using a multi-input technique. The k^{th} fuzzy rule R^k is then produced as follows after inputs xi, i=1, 2,..., n, and outputs yj=1, 2,..., m are assigned:

$$R^k: IF x_1\ is\ F_1^k\ and\ \ldots .\ x_n is F_n^k \quad (1)$$

$$\text{Then},\ y_1 is\ w_1^k\ and\ \ldots y_m\ is\ w_m^k \quad (2)$$

k^{th} fuzzy rule and i^{th} input make up the fuzzy set F^k_i. It assigns various linguistic labels to each element in the input matrix based on membership functions. Grade, which is determined by the fuzzy membership function, describes the input node's belonging to a particular fuzzy set. An example of the fuzzy set ($\widehat{X_\iota}$)is

$$\widehat{X_\iota} = fuzz(\frac{x_{ij}}{Mx_{ij}}) \quad (3)$$

where Xi represents the input matrix and Mx stands for the center of the input fuzzy membership function. Blood pressure, heart rate, alcohol, and SpO2 levels are taken into consideration as membership functions. These inputs are combined with a predetermined linguistic rule-base to create a fuzzy output.

Fuzzy reduces uncertainty while neural network reduces noise in the original data in FRCNN. A fully connected layer and a convolutional layer make up the proposed FRCNN's structure. Three stages are experienced by the convolutional layer: the stages of pooling, nonlinearity, and convolution. The fuzzy logic representation is first created by processing the incoming data in the fuzzification layer. Fuzzified convolution kernels are present in the fuzzy convolutional step, which is where the fuzzy representation becomes convoluted. The process of obtaining higher level fuzzy features from input spatial information through the min-max composition of fuzzified kernels is known as fuzzy convolution. The characteristics acquired through pooling are used to create the crisp values during the defuzzification layer. Finally, a fully connected layer operates as the FRCNN's output classifier. The cross entropy loss function is used to train the model's parameters.

Equation (2) provides the updated weight:

$$W_f(k+1) = W_f(k) - \delta_{fc}\frac{\partial CE}{\partial W_f} \quad (4)$$

The weight matrix in the fully linked layer is represented by Wf. CE id expressed as

$$CE = -\frac{1}{N}\sum_{n=1}^{N}[z_n \log(\widehat{Z_n}) + (1-z_n)\log(1-\widehat{z_n} \quad (5)$$

If the number of samples is indicated by N, the target is given as z, and the classifier's output is given as z ̂. Four inputs and one output make up the rule-base for heart attacks. The output is fuzzified into four fuzzy signals: very

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low (VL), low (L), medium (M), and high (H). The output indicates the probability to experience a heart attack. Two variables are generated from the first input, alcohol (Alc): low (L) and high (H). The SpO2 level, the second input, is fuzzified into three variables: normal (N), medium (M), and low (L). Blood pressure (BP), the third input, is fuzzy-coded as low (L), normal (N), and high (H) signals. Heart rate, the fourth input, is similarly fuzzified like the third input. Those with medium and high risk of a heart attack are identified by the output membership functions. Experts can also create rule bases for particular diseases, from which the system generates a list of probable cases.
Hence, in this way, this FRCNN model classifies the diseases on huge volumes of big data.

IV. RESULT ANALYSIS

In this section, A Novel Big Data Approach Using Fuzzy Rule Based Multilayer Perceptrons is implemented. This section evaluates the model's results analysis that was presented. The accuracy, precision, recall, and F1-score of the model that is being given are used to evaluate its performance. The comparison of performance is displayed in Table 1.

Table 1: Performance Comparison

Metrics/Model	**Fuzzy Clustering**	**FRCNN**
Precision (%)	89.3	94
Recall (%)	90.8	95.23
Accuracy (%)	90.5	95.4
F1-score	90.2	94.32

Compared to fuzzy clustering techniques, presented FRCNN has shown better performance. The Figure 2 shows the Precision and Recall comparison.

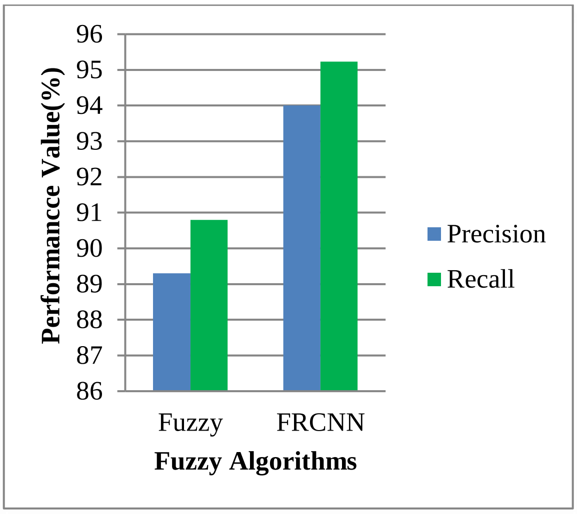

Figure 2: Precision and Recall Comparison

Figure 2 shows performance values on the y-axis and fuzzy algorithms on the x-axis. The FRCNN has obtained high precision and recall than fuzzy clustering model. The Figure 3 shows Accuracy Comparison.

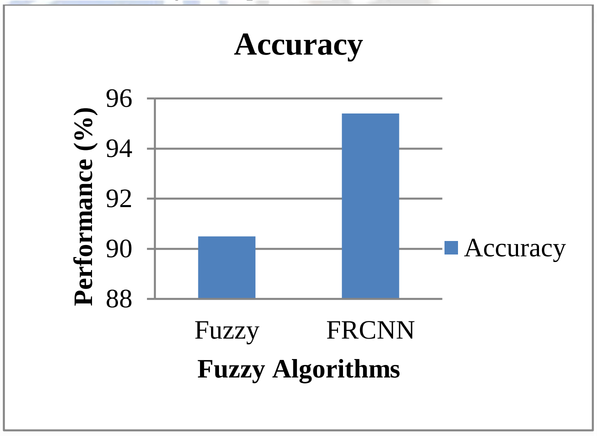

Figure 3: Accuracy Comparative Graph

Compared to fuzzy clustering model, the FRCNN model has achieved better accuracy for big healthcare data classification. The Figure 4 shows the F1-score comparison graph.

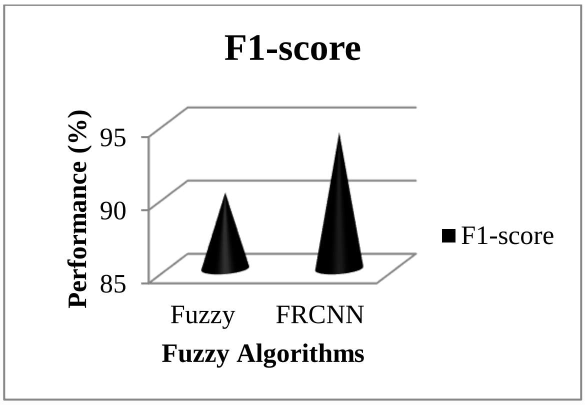

Figure 4: F1-score Comparative Graph

The FRCNN has better F1-score than fuzzy clustering model for big healthcare data classification. This approach classified the huge volumes of healthcare data very accurately and obtained better results than earlier models.

V. CONCLUSION

Healthcare applications produce huge quantities of data that vary in volume, variety, velocity, veracity, and value. As a result, effective mining approaches have become crucial for context-aware data processing, retrieval, and categorization. To do this, A Novel Big Data Approach Using Fuzzy Rule Based Multilayer Perceptrons is presented in this analysis. Big data provided tools for data accumulation, management and analysis of huge volumes of unstructured and structured healthcare data. Firstly, patient data is collected which includes patient personal details, health checkup details, previous and family disease history, etc. The data is preprocessed using PCA to remove the noise and improve the performance of the classifier. The patient data is categorized as normal and disease using the FRCNN (Fuzzy Region based Convolutional Neural Network) classifier. This approach identified and classified various disease using fuzzy rules. The accuracy, precision, recall, and F1-score of this method is validated. Compared to earlier models, the FRCNN model has obtained better performance and shown significant performance for huge volumes of big healthcare data.

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