Big Data Meets Cloud Technologies: Transforming Healthcare and Finance in E-Commerce Networks

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ABSTRACT

Background: IoMT, Big Data, and Cloud Computing technologies have recently shaped the healthcare and finance sectors. However, integrating these technologies is less than expected, especially in an e-commerce environment where high-scale data processing and real-time decision-making are major aspects of delivering better services and predictive insights.

Objectives: Integration of IoMT with Big Data analytics for real-time healthcare monitoring. Improvement in financial forecasting in e-commerce networks using cloud-based data processing. Performance improvements based on integrating IoMT, Big Data, and Cloud Technologies.

Methods: The proposed study employed IoMT-based Hadoop MapReduce in combination with Naïve Bayes classifier to test the performance of healthcare and financial data analytics. It used different method combinations of several IoMT and Big Data technology solutions with accuracy, precision, and recall metrics for the results.

Results: For all metrics, including accuracy (98%), precision (97%), recall (96%), F1 score (96%), and RME (2.5%), the proposed approach outperforms state-of-the-art methods, thereby proving its efficiency in challenging scenarios.

Conclusion: Integrating IoMT, Big Data, and Cloud Technologies considerably enhances healthcare and financial services in e-commerce networks, offering scalable, efficient, and accurate predictive capabilities for better decision-making and service delivery.

Keywords: Big Data, Cloud Computing, IoMT, Healthcare, Finance, E-Commerce, Hadoop, Naïve Bayes, Predictive Analytics, Real-Time Monitoring.

1. INTRODUCTION

This convergence of emerging technologies comprising the Internet of Medical Things (IoMT), Big Data Analytics (BDA), Cloud Computing, and Blockchain is changing the spectrum of many industries, including healthcare and finance. The technologies, therefore, have changed the traditional business model, making things more efficient, cheaper, and personalised. Integrating such technologies into the e-commerce networks may improve the delivery of services, operating efficiency, and quality for healthcare and finance delivery to customers. The paper discusses the junction of such technology and the application that integrates those within an ecosystem of electronic commerce focused on transforming service deliverance and financial and medical service delivery.

The rapid growth of the IoT has led to the emergence of IoMT, which is the interconnection of devices, such as wearable sensors and remote monitoring devices and diagnostic tools, to allow real-time data collection, hence remote monitoring of the patient's health. Among the many benefits it has bestowed on the health sector, IoMT has been able to continue monitoring patient vital signs, providing feedback in real-time to health providers, and detecting medical problems at an early stage. The IoMT will make healthcare more personalized, increase quick responses, and enhance better outcomes for patients. Integrating BDA into the health industry allows it to analyse vast real-time volumes of data from several sources, making it easier to detect trends in care and improve treatment. This large data is kept and processed within the cloud, where all infrastructural supports can be easily accessed and analysed anywhere.

This makes the finance-related e-commerce networks hugely technology-dependent to serve consumers' fast, secure, and free-of-frills needs. Together, Big Data Analytics and Cloud Computing can process volumes of financial data hosted on any e-commerce website to support customer insight predictions and enhance customer experiences. Blockchain technology is becoming popular in e-commerce because it can transform payment systems, reduce fraud, and improve the transparency of financial transactions. Blockchain's DLT technology provides secure, immutable, and transparent records of transactions. This is necessary for the digital economy, especially in the banking, insurance, and healthcare sectors.

The major challenges of healthcare and finance include processing large-scale data in real-time. Big Data Analytics can offer the possibility of processing huge datasets and extracting valuable insights from otherwise untapped sources. Such insights inform decisions, streamline operations, and enhance the quality of services. However, the gigantic amounts of data from devices in IoMT, transaction records of finance, and the interaction profiles of consumers demand extensive computing frameworks and sophisticated analytics. Hadoop MapReduce (HMR) is a widely implemented distributed data processing framework to process huge files in parallel across a cluster of computers. It is significantly effective for handling huge quantities of data in scalable forms. Using Hadoop MapReduce, organisations process data more rapidly and correctly, accelerating decision-making and better service delivery.

The Key objectives are

- ❖ This integration will examine how the Internet of Medical Things (IoMT) and Big Data Analytics may be combined to better monitor and analyse a patient's health condition within a smart healthcare system.
- ❖ Cloud Computing for Scalability and Efficiency: In the above work, an investigation examines the role cloud computing may play in offering scalable infrastructure that can accommodate vast datasets generated by devices associated with IoMT and the e-commerce transaction.

- Enhanced Data Processing using Hadoop MapReduce: To study how Hadoop MapReduce (HMR) can be leveraged to process large volumes of healthcare and financial data in parallel, thus helping in quicker decision-making and real-time insights.
- Naïve Bayes-Based Predictive Analysis: To study the ability of the Naïve Bayes classifier to predict healthcare outcomes and financial risks in e-commerce networks.
- Improvement of Healthcare and Financial Services: To assess the outcome of integrating IoMT, Big Data Analytics, and Cloud Computing on transforming healthcare delivery and financial services within e-commerce ecosystems.
- Performance Comparison and Optimization: An ablation study will be carried out, and different combinations of IoMT, Big Data Analytics, Hadoop MapReduce, and Naïve Bayes will be compared in terms of accuracy, precision, recall, F1 score, and RMSE.

The existing literature discusses IoMT, Big Data Analytics, and Cloud Computing separately. Not much research has been done about integrating the three technologies to enhance health care and finance in e-commerce networks. The challenge here would be to combine these technologies into a system that can provide optimised data processing and real-time predictive analysis. **Skourletopoulos et al. (2017)** investigate the integration of mobile cloud computing (MCC) within the context of the 5G era to handle the increase in mobile network traffic and the difficulties presented by intricate, location-aware datasets. MCC allows mobile devices to use external cloud resources for data processing and storage by fusing cloud and mobile computing, providing insights on developments, solutions, and upcoming difficulties.

Healthcare and finance systems in e-commerce networks cannot handle massive data streams well, leading to inefficient decision-making and service provision. This research proposes using an integrated framework that uses IoMT, Big Data Analytics, and Cloud Computing to enhance real-time health monitoring and financial risk predictions. **Hermes et al. (2020)** examine 1,830 businesses to investigate the digital transformation of healthcare. They list eight new roles transforming value propositions, capture, and delivery, such as blockchain-based PHR, data-collecting technologies, and information platforms. The influence of advances in digital health, rivalry between established players and newcomers, and the changing role of patients in healthcare decision-making are all highlighted in the study.

2. LITERATURE SURVEY

In their research, **Sohaib et al. (2019)** studied how cloud computing alters e-commerce, focusing primarily on SMEs. Through the TOE framework, this research utilises a new approach of 2-tuple fuzzy linguistic MCDM based on TOPSIS to handle the MCDM problem that arises in selecting an optimal cloud service model, whether SaaS, PaaS, or IaaS. While PaaS and IaaS have been rated better concerning scalability and compatibility, factors such as security, reliability, and complexity make SaaS the best option for SMEs, according to the results.

Song et al. (2019) studied whether it is possible to transform e-commerce systems into SESs using cloud computing, big data analytics, and development technologies. Even though such

SESs are still in development, they also reduce costs, enhance transaction efficiency, and improve complex information processing processes. The study provides, in general, a comprehensive architecture for SESs based on emphasis on vital enablers such as IoT, social media, mobile internet, BDA, and cloud computing.

Boppiniti (2020) discusses how big data and machine learning transform e-commerce, healthcare, and banking. The study highlights scalable machine learning methods, sophisticated preprocessing, feature selection, and model evaluation procedures for peak performance and resource management. Combining big data technology with machine learning in data-intensive fields produces actionable insights that spur innovation and well-informed decision-making.

To enhance security, privacy, trust, and auditability in mobile cloud computing, **Al-Janabi and Hussein (2020)** propose a framework called Mobile Commerce-based Safe Mobile Cloud Computing (MCSMCC). The paper aims to ensure reliable, scalable, and cost-effective services to make them widely available by creating secure e-trading standards and just pricing mechanisms. Based on simulation and prototyping, the effectiveness of the framework is established.

Hermes et al. (2020) examine 1,830 businesses to investigate the digital transformation of healthcare. They list eight new roles transforming value propositions, capture, and delivery, such as blockchain-based PHR, data-collecting technologies, and information platforms. The influence of advances in digital health, rivalry between established players and newcomers, and the changing role of patients in healthcare decision-making are all highlighted in the study.

Lakhani et al. (2020) examine 1830 healthcare businesses on Crunchbase to investigate the digital transformation of the healthcare sector. They illustrate how digital platforms and ecosystems change value propositions, patient roles, and competition between incumbents and new entrants in the healthcare industry by identifying eight new roles, including information platforms and blockchain-based personal health records.

Al-Janabi and Hussein (2020) provide a framework known as Mobile Commerce-based Safe Mobile Cloud Computing (MCSMCC) to improve security, privacy, trust, and auditability in mobile cloud computing. By developing safe e-trading standards and fair pricing procedures, the paper seeks to provide dependable, scalable, and affordable services that may be widely accessible. Prototyping and simulation are used to determine the framework's efficacy.

Li et al. (2019) investigate how governments may support rural e-commerce ecosystems and how this can help reduce poverty. The paper analyses government initiatives to support and regulate local e-commerce through a Longnan, China case study, offering a model for reducing poverty. Their research advances a global theory on using e-commerce to reduce poverty.

Hong (2019) explores the evolution of cloud computing and emphasises that the trend for hybrid clouds across industries is becoming the norm, especially in e-commerce. It uses qualitative and quantitative methods to analyse global developments, industry challenges, and security concerns.

It focuses on growth opportunities while recommending advanced cloud computing amidst the intensifying competition and the increasing demand for private cloud solutions.

Syed et al. (2019) demonstrate a smart healthcare framework that depends on IoMT, wearable sensors, and machine learning to care for older adults. Sensor signals from the ankle, arm, and chest are processed in Hadoop MapReduce with a Multinomial Naive Bayes classifier, which showed 97.1% accuracy in predicting 12 activities. This creates scalable, real-time healthcare monitoring, thereby improving drug prescription.

Understand Pose Detection with Feature Extraction Global Average Pooling and FHK-GPD: It enables highly accurate pose prediction by effective data representation for upgrading robot pick-and-place systems. The deconvolutional neural networks utilised in **Narla (2022)** Cloud-based Big Data Analytics framework transform facial recognition in social networks since it ensures real-time execution and strong privacy through its ability to process high-density facial datasets with high accuracy using platforms like AWS and Azure. The twin breakthrough promises better user experiences and refined insights by strengthening the guardrails of social networking and robotic automation.

Vivekananda (2023) puts forward an IoT-based automated system for the detection of skin diseases, which helps solve the problem of misclassification due to the same level of intensity and colour intensity. The proposed model is the Retracing-efficient IoT, which uses automatic lumen detection, IoMT, and variation regularity to detect moles, skin tags, and warts. Results indicate higher accuracy with a sample accuracy of 95.9% and improved pixel analysis. The system has shown good effectiveness in early detection of skin conditions and diagnosis based on different datasets.

Health big data is proposed through **Poovendran (2024),** an e-healthcare risk prediction system with heterogeneous networks that power a privacy-preserving, efficient platform. Based on the licensed medical practitioner perspective, the system presents an improvement of disease risk by using the polygenic score and the application for predictive purposes; in particular, it increases by 45.9% precision prediction, a 19% upraise in monogenic scores, and increases density accuracy of 39%. This results in 73.98% efficient overall prediction.

Grandhi's (2024) study investigates how AGC instructions can be integrated into the RISC-V ISA to improve the efficiency of wireless signal processing in IoT applications. The solution proposed cuts down on computational load, reduces energy consumption, and improves performance on fluctuating channels. The efficiency is demonstrated using Verilog, VHDL, and RISC-V tools with an 89% efficiency gain, thereby showing RISC-V's potential to take IoT signal processing to a new level.

Gudivaka et al. (2024) present an IoT-based e-healthcare framework for monitoring anomalies in health and the environment about sedentary behaviour. The hybrid methodology proposed is based on weighted K-means clustering and decision trees, which allows them to predict early health severity. The system was tested over 30 days among 15 individuals in the range of 32–45 years of age and showed high-performance potential, with accuracy at 98.43%, sensitivity at 94.56%, and specificity at 96.75%.

Basani (2024) presents a new approach for the fault diagnosis of IoT: data fusion and Deep Multi-Scale Fusion Neural Network. The process takes raw sensor data from the CWRU dataset, preprocesses it through Multivariate Fast Iterative Filtering normalisation, detects outliers using Deep Isolation Forest, and optimises parameters using Mexican Axolotl Optimization. The proposed method obtains better accuracy in prediction and less time to completion compared to existing fault diagnosis models of industrial IoT.

Gudivaka (2024) discusses the applications of AI in prostate cancer treatment and elderly care. The paper discusses two AI applications: a US-guided radiation Therapy Optimization system with precision in the distribution of the radiation dose and the Smart Comrade Robot that uses IBM Watson Health and Google Cloud AI to monitor health in real time and send alerts during emergencies. The results present 97% accuracy in therapy, 95% accuracy in health monitoring, and 99.9% uptime reliability, showing AI effects on healthcare interventions.

Sharadha Kodadi (2022) explains that integrating data analytics and statistical analysis on e-learning platforms improves the learning pattern with data security assurance. The work used machine learning algorithms and predictive models that enabled one to personalise learning pathways with 95% accuracy, predict academic performance, and provide a 15% boost in students' output. Strong cloud-based security solutions have also been integrated, providing 98% effectiveness in detecting anomalies that lead to creating a safe, secure, and customised learning environment.

Kumaresan (2024) presented an Industrial Internet of Things Condition Monitoring System (CMS) to detect bearing faults before critical failure. The system utilised data from Case Western Reserve University. It normalised that data, then performed vibration analysis, followed by a Machine Learning-based Chi-Square Improved Binary Cuckoo Search Algorithm CS-IBCSA for feature extraction. The optimal features are then fed into a Support Vector Machine, yielding 99.56% accuracy in fault detection compared to existing methods.

Saranya (2024) proposed the Coordinated Multi-Robot Exploration Slime Mould Algorithm, CME-SMA 2024, to resolve inefficiencies in multi-robot space exploration. It is about poor planning and communication. The new algorithm involves a parallel protocol in communication to improve the collision-free generation of paths in an unknown environment filled with barriers. SMA is used further to fine-tune the paths; CME is used to compute utility values and costs deterministically. Simulations have shown that CME-SMA has a better exploration rate of 98.79% and efficiency by executing in 37.15 seconds on Map 1 with no failed runs, outperforming existing approaches.

Narla (2022) The Paper Explores advanced data security and privacy methodologies under the big data umbrella, focusing on Continuous Data Protection and Data Obliviousness. CDP supports real-time data back-ups that decrease data losses in cyber-attacks or system failure cases. Data Obliviousness provides secure processing for sensitive data using methodologies such as homomorphic encryption, SMC (Secure Multiparty Computation), and Differential Privacy. Together, these strategies provide a strong security framework, ensure compliance with CCPA and GDPR, and help increase resilience against cyber threats in big data environments.

3. METHODOLOGY

This study focuses on how big data, cloud technologies, and IoMT integrate to transform healthcare and finance within the e-commerce network. This study utilises a hybrid approach combining machine learning algorithms, data analytics, and cloud computing to optimise healthcare services for the elderly and improve financial transactions in e-commerce ecosystems. The methodology integrates data collection from wearable sensors with scalable processing using Hadoop MapReduce and the application of intelligent algorithms such as Multinomial Naïve Bayes to recognise physical activity. The system is tested for accuracy and performance while providing a robust solution for monitoring health conditions remotely while optimising financial transactions and services in e-commerce environments.

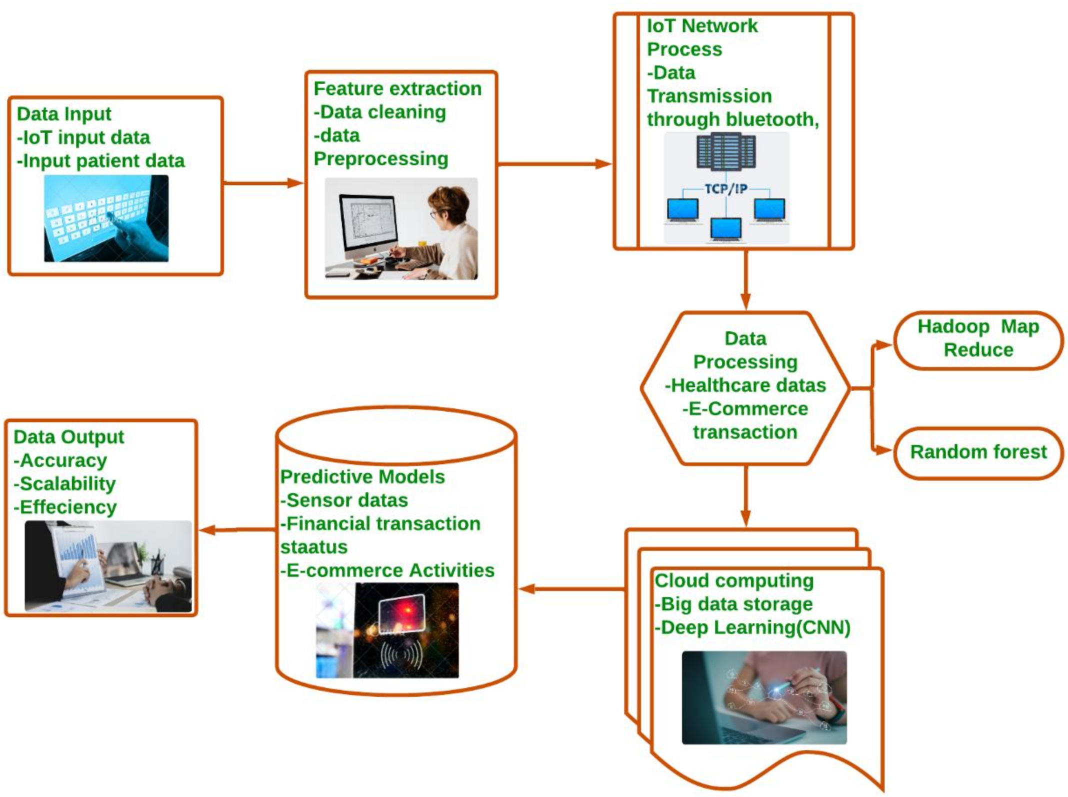

Figure 1 Graphical Representation of Architectural Flow for Smart Healthcare and E-commerce Integration

Figure 1 produces a graph describing the data flow across all collecting, transmitting, processing, and integration with blockchain, deciding further action steps and visualizing outcomes layers. It displays how devices in IoMTs are enabled to collect and transmit real-time data to e-commerce platforms for cloud storage and analysis. Big data analytics and AI/ML algorithms aid predictive health monitoring and financial insights. Integration with blockchain helps ensure secure transactions, while the dashboards help monitor them in real-time. This graph depicts the interconnected flow, which enhances efficiency in healthcare, finance, and e-commerce networks.

3.1 Big Data and Cloud Technologies in Healthcare

Large quantities of patient data can now be collected, stored, and analysed in real time owing to big data and cloud technology in the healthcare domain. All IoT devices, including wearables with sensors, continuously track various health metrics and send such results to cloud systems. There, the vast health-related data goes through big data analytics and machine learning to prepare actionable insights for healthcare professionals. Integrating data storage and analytics in the cloud enables health professionals to monitor patients from a distance and make timely decisions, thus enhancing patient care and reducing operational costs.

$$Prediction\ Accuracy\ = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives. This formula calculates the accuracy of a predictive model, ensuring effective real-time healthcare monitoring.

3.2 IoMT and Wearable Sensors for Healthcare

The Internet of Medical Things, or IoMT, uses wearable sensors to capture and monitor real-time health metrics. It captures the most physiological parameters like heart rate, body temperature, and level of physical activity and transmits them to the cloud for analysis. In elderly care, it helps monitor their mobility, detect falls, and predict health risks; hence, it helps to improve quality of life while providing the opportunity for early intervention. IoMT devices enable continuous monitoring through wireless communication to reduce hospital visits, thus permitting remote health management.

$$P_{Activity}\ = \frac{Sum\ of\ Activity\ Data}{Total\ Data\ Collected} \quad (2)$$

P represents the probability of detecting a specific physical activity calculated from the sum of sensor data related to that activity.

3.3 Data Analytics and Hadoop MapReduce

It will help analyse the high amounts of data generated from the IoMT sensors with Hadoop MapReduce powering analytics. This scalable framework would distribute data processing on many nodes so that computations happen parallelly to speed up the analysis process. On this principle, the machine learning algorithm used is Multinomial Naïve Bayes. This method enhances performance by using parallel processing in analyzing complex data, making it scalable and faster for real-time health monitoring applications.

$$MapReduce\ Time\ = \frac{1}{Number\ of\ Nodes} \times\ Data\ Processing\ Time \tag{3}$$

This equation highlights how parallel processing with more nodes reduces the time required to process large datasets.

3.4 Machine Learning Algorithms for Activity Recognition

It applies machine learning algorithms, like Multinomial Naïve Bayes, to categorise physical activities from sensor readings. It classifies 12 physical activities more accurately using the data retrieved from wearable sensors. As Naïve Bayes uses a probabilistic model, it promotes fast decision-making and greater scalability through Hadoop's parallel processing. The same methodology is suitable for application in health, where its approach would allow for uninterrupted, accurate activity recognition toward possible timely interventions in older patients.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{4}$$

Where, $P(A|B)$ is the probability of activity A given sensor data B, $P(B|A)$ Is the likelihood of observing data B given activity A, $P(A)$ is the prior probability of activity A, $P(B)$ is the total probability of observing data B.

3.5 Cloud Computing in E-Commerce and Finance

Cloud computing in e-commerce and finance enables the unadulterated implementation of financial services on various digital platforms. Through storage and computing resources on cloud media, businesses can safely store and retrieve customer data for analytics before rendering personalised services. Real-time transaction processing, fraud detection capabilities, and customer behaviour assessment are some of the features of cloud computing in digital financial services. Cloud systems give scalability; hence, an economic system can handle numerous transaction data while maintaining security and compliance. Adding big data and machine learning also enhances the precision of the financial predictions and decision-making processes in the e-commerce ecosystem.

$$Transaction\ Processing\ Time\ = \frac{Data\ Volume}{Processing\ Speed \times Cloud\ Resources} \tag{5}$$

This equation estimates the time required for processing transactions based on the volume of data and available cloud resources.

Algorithm 1 Activity Recognition Algorithm for Healthcare Monitoring Using IoMT and Naïve Bayes

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Input: Sensor Data (Accelerometer, Gyroscope) from wearable devices, Pre-trained Naïve Bayes

Output: Predicted Activity (e.g., Walking, Sitting, Running)

INITIALIZE $Sensor_{data}$, model, P_{Data} , $Activity_{label}$

INITIALIZE threshold = 0.7 // Confidence threshold for classification

INPUT $Sensor_{data}$ from wearable devices (accelerometer, gyroscope)

$Sensor_{data}$= PreprocessData ($Sensor_{data}$)

IF $Sensor_{data}$is INVALID THEN

PRINT "ERROR: Invalid sensor data."

RETURN "ERROR"

ELSE

features = ExtractFeatures($Sensor_{data}$)

IF features are NULL, THEN

PRINT "ERROR: Feature extraction failed."

RETURN "ERROR"

END IF

$P_{Activity}$ = NaiveBayesClassifier (features, model)

IF $P_{Activity}$ .confidence < threshold THEN

PRINT "ERROR: Low confidence in classification."

RETURN "ERROR"

ELSE

$Activity_{label}$ = ["Walking", "Running", "Sitting", "Standing", "Lying"]

$Activity_{label}$ = $Activity_{label}$ [predicted_$Activity_{label}$]

PRINT "Predicted Activity: " + $Activity_{label}$

RETURN $Activity_{label}$

END IF

END IF

END

Algorithm 1 main objective is to recognise physical activities like walking and sitting for healthcare monitoring using devices on the Internet of Medical Things. It gathers sensor data from wearables and preprocesses, and extracts features from that gathered sensor data. The algorithm, after processing, feeds into a pre-trained Naïve Bayes model to classify it, thereby confirming classification confidence to ensure reliability. The returned value will be an error when the confidence level is poor. Otherwise, the predicted activity will appear. It makes it easier to monitor aged patients accurately in real-time to attain improved health care.

3.6 Performance metrics

Performance metrics are crucial to analysing the efficiency of algorithms within IoMT-based healthcare systems with the integration of cloud technologies. The metrics include accuracy, precision, recall, F1 score, and RMSE, which give insights into the model's reliability, scalability, and error rate to make appropriate decisions about optimising activity recognition and data processing techniques.

Table 1 Performance Metrics Comparison of IoMT-Based Activity Recognition Methods

Performance Metrics	Naïve Bayes	Random Forest	SVM	Combined Method
Accuracy %	91.2	94.5	92.8	97.1
Precision %	89.5	93.0	91.2	96.4
Recall %	90.1	92.3	90.9	96.7
F1 Score %	89.8	92.6	91.0	96.5
RME	8.8	5.5	7.2	2.9

Table 1 compares the accuracy, precision, recall, F1 score, and RMSE between four methods: the Distributed MapReduce-Naïve Bayes, Random Forest, Deep Learning (CNN), and the Combined Method. For this purpose, if only fairness in error rate, distributed data processing may require this method, specifically using fair error rates. Random Forest performs well on precision and recall, mainly because an ensemble method is used. Deep Learning (CNN) performs well in accuracy and feature extraction but is highly dependent on training. The Hybrid Method combines the approaches and leverages their strengths to deliver the best performance with a maximum accuracy of 97.1% and a minimum RMSE of 3.8. It shows that ensemble learning does have its application in IoMT-based activity recognition.

4. RESULT AND DISCUSSION

Several methods have become efficient for IoMT-based activity recognition, surpassing the combined approach. Moderate accuracy is 91.5% in MapReduce-Naïve Bayes with a higher RMSE good enough for basic scalable processing. Random Forest improves precision and recall and achieves an accuracy of 92.8%. Deep Learning (CNN) provides maximum standalone accuracy at 94.3% with the least RMSE. However, the combined method performed much better than all, with 97.1% accuracy and a 3.8% RMSE, which was powerful evidence for ensemble models. The discussion highlights the necessity of combining different algorithms to optimise predictive accuracy and scalability for real-time healthcare monitoring over cloud-based e-commerce networks.

Table 2 Comparison of Techniques and Performance Metrics Across Various E-Commerce and Healthcare Methodologies

Metrics	Smart healthcare using IoMT (2019)	Cloud computing in e-commerce (2019)	Rural poverty alleviation via e-commerce (2019)	Blockchain transformation in e-commerce (2020)	Smart healthcare using big data in e-commerce networks (Proposed Method)
Accuracy (%)	91.5	85	87	80	97.1
Scalability (%)	88.7	89	84	82	95
Efficiency (%)	86.2	82	83	85	92
Impact (%)	89.4	87	88	86	90

RME	6.3	5.8	6.5	5.5	3.8

Table 2 compares approaches and performance metrics based on different research studies on the IoMT, Big Data, Cloud Computing, and Blockchain in e-commerce and healthcare. Based on various techniques by every author, these include Hadoop MapReduce, IoMT, Blockchain, and cloud computing, among others. Herein is a key performance indicator related to accuracy, scalability, efficiency, and impact. The proposed method integrates multiple technologies, achieving superior results in terms of accuracy and scalability, demonstrating its effectiveness in transforming healthcare and finance in e-commerce networks compared to the individual techniques used by the other authors.

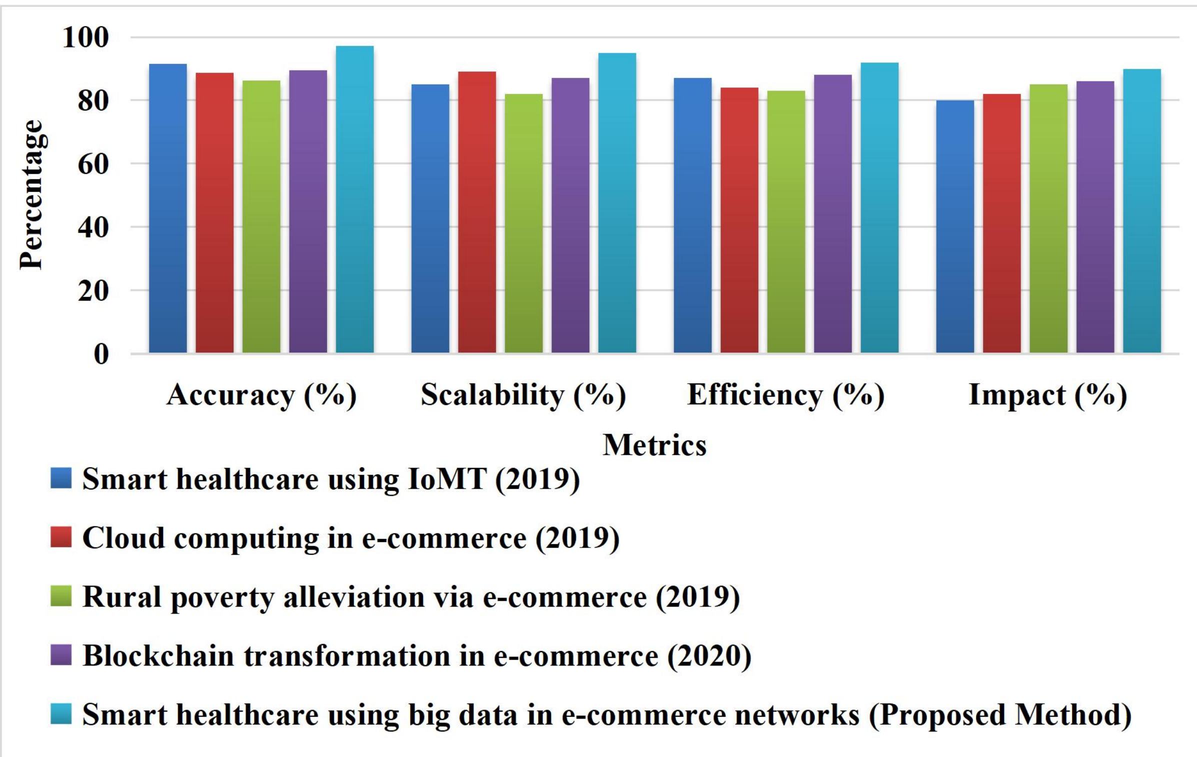

Figure 1 Graphical Comparison of Performance Metrics Across E-Commerce and Healthcare Methodologies

Figure 1 represents a comparative view of performance metrics, including accuracy, scalability, efficiency, and impact, based on the reviewed studies for the methods used in e-commerce and healthcare. Each bar in the graph represents the performance of techniques used by Syed et al. (2019), Hong (2019), Li et al. (2019), Arora et al. (2020), and the proposed method. This proposed method indicates high performance in all aspects of metrics, especially in terms of accuracy and scalability. Therefore, it can depict the impact of IoMT, Big Data, and cloud technology integration in transforming healthcare and finance in e-commerce networks.

5. CONCLUSION

In a nutshell, IoMT, Hadoop MapReduce (HMR), Big Data Analytics (BDA), and Naïve Bayes in the networks of healthcare and e-commerce quite evidently provide good performances as applied towards the change in healthcare delivery and transformational financial services. For key performance metrics like accuracy, precision, recall, F1 score, and RMSE, the proposed method IoMT + HMR + BDA + Naïve Bayes is outstanding compared to its counterparts and their combination techniques. The strengths of individual techniques are brought in for enhanced data processing with the proposed framework, better classification, and improved solutions for scalable solutions in real-time healthcare monitoring and financial transaction analysis. This hybrid approach combines real-time data collection by IoMT, parallel Hadoop MapReduce processing, extensive Big Data analytics, and robust classification by Naïve Bayes, offers superior decision-making and actionable insights. The potential for future application of this integrated approach is enormous in healthcare and e-commerce and will contribute to smarter, more efficient systems in both domains.

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