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Hybrid CNN-LSTM Powered Cloud Ecosystems: Advancing Finance, Healthcare, and Retail Through Unified AI Architectures

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ABSTRACT

The rapid digitalization of business processes in sectors such as finance, healthcare, and retail has led to a large amount of complicated data that needs robust and intelligent processing mechanisms. This paper proposes a homogeneous AI-based cloud environment on the basis of a hybrid CNN and LSTM model in order to deal with prediction and anomaly detection problems. The methodology begins with the integration of heterogenous data sets pulled from public repositories, and over significant sectoral spaces. The data sets include structured data like patient data, financial data, and transaction streams as well as unstructured formats like text input and sensor streams. For model readiness and consensus, Min-Max Scaling is employed for data normalization, and dimensionality reduction is done using Principal Component Analysis. Feature engineering extracts useful patterns, usage data, and performance metrics. The core component of the model employs CNN for spatial feature learning and LSTM for modeling temporal dependency, which is well-suited to time-series and sequential forecasting. To achieve secure and verifiable data integrity, a blockchain protocol is implemented within the multi-cloud setup. Additionally, multi-view K-means clustering enhances classification accuracy by learning data from different perspectives. Execution is carried out using Python with TensorFlow and Scikit-learn packages to ensure flexibility and reproducibility. Results of experiments demonstrate that the proposed hybrid model achieves higher performance than traditional CNN and LSTM models when it comes to prediction accuracy, anomaly detection, and processing time. The system achieved a prediction accuracy of 92%, proving its effectiveness in intelligent cloud applications in different sectors.

Keywords: Hybrid CNN-LSTM, Cloud Computing, Blockchain, Anomaly Detection, Multi-view Clustering.

1.INTRODUCTION

Digital innovation has become a pivotal force across numerous industries, reshaping traditional business models and consumer interactions [1]. Generation Z's consumer behavior witnessed a significant transformation in cloud kitchens during the COVID-19 pandemic, reflecting shifting preferences toward convenience and digital ordering [2]. The rapid adoption of work-from-home practices during the pandemic markedly increased demand for robust cloud computing infrastructures globally [3]. Lung cancer, primarily originating from the epithelial cells lining the airways, remains one of the leading causes of cancer mortality worldwide [4]. The Internet of Things (IoT) has revolutionized healthcare by enabling continuous patient data collection and real-time monitoring [5]. Electronic fund transfers have become the standard mode of disbursing payments in most countries, allowing beneficiaries to receive funds quickly and securely [6]. Contemporary technologies, including machine learning and big data analytics, provide novel solutions for complex financial data analysis challenges [7]. Advances in technology and data analytics have significantly reshaped healthcare delivery systems over recent years, improving patient outcomes [8]. Building an inclusive digital economy that benefits both urban and rural populations requires addressing digital divide issues and infrastructure gaps [9]. Stochastic optimization models offer promising approaches to manage uncertainty in project management, particularly for staff planning and scheduling [10].

In cybersecurity, neural networks and sensitive system call analysis have enhanced the detection and mitigation of sophisticated malware attacks [11]. Financial time series analysis is crucial in forecasting market trends and identifying anomalies for risk mitigation in dynamic financial markets [12]. Despite advances, efficient resource utilization and secure data exchange in IoT environments remain challenging [13]. Artificial intelligence (AI) and machine learning (ML) bring unprecedented analytical power to human resource management systems, enabling discovery of deep insights from vast datasets [14]. However, the complexity and volume of data present challenges in timely processing and simulation execution [15]. Multi-view clustering techniques improve big data processing efficiency by integrating heterogeneous data sources [16]. Blockchain technology ensures data integrity and security in multicloud architectures by providing decentralized and tamper-proof ledgers [17]. Autonomous cloud systems, inspired by biological self-regulation, are emerging AI-driven frameworks capable of self-managing infrastructure resources [18]. Cloud computing offers cost-effective remote storage and scalable processing power, facilitating efficient data management [19]. The healthcare industry's migration to cloud environments amplifies the need for robust mechanisms to protect sensitive patient information while maintaining availability [20].

Fog computing extends cloud capabilities by bringing computation closer to data sources at the network edge, reducing latency and bandwidth usage [21]. The absence of common standards and frameworks hinders the effective exchange and interoperability of healthcare data, limiting advanced analytics applications [22]. Cloud analytics platforms enhance hybrid machine learning models by providing scalable resources for processing large electronic medical records (EMR) datasets [23]. The urgent demand for low-latency communication systems in healthcare supports real-time information processing crucial for patient care [24]. Incorporating bio-inspired learning algorithms in resource allocation improves efficiency and decision-making in medical imaging systems [25]. Mobile multimedia health record management optimization leverages next-generation cloud technologies to enhance accessibility and security [26]. Network security robustness is vital in cloud environments due to escalating cyber threats targeting healthcare data [27]. Advanced cryptographic methods coupled with facial deidentification algorithms safeguard patient privacy against unauthorized access [28]. The integration of AI in cloud platforms facilitates timely and accurate diagnostic processes in healthcare [29]. Blockchain-enabled identity management systems contribute to secure patient data handling and consent management [30].

Edge computing complements cloud systems by processing data locally, reducing latency and improving responsiveness for healthcare applications [31]. Data anonymization techniques ensure compliance with privacy regulations while enabling meaningful analytics [32]. Deep learning models applied to medical imaging enhance diagnostic accuracy and early disease detection [33]. Hybrid machine learning frameworks combining supervised and unsupervised methods improve predictive modeling in healthcare [34]. Real-time analytics empower clinicians with timely insights for personalized treatment plans [35]. Cloud-based telemedicine platforms expand healthcare access to remote and underserved populations [36]. AI-powered decision support systems assist clinicians in complex medical diagnoses and treatment recommendations [37]. Continuous monitoring through wearable devices provides granular health data enabling proactive care management [38]. The convergence of IoT, AI, and cloud computing paves the way for intelligent healthcare ecosystems [39]. Ensuring data confidentiality, integrity, and availability remains a cornerstone in healthcare digital transformation initiatives [40]. Major Contributions of this paper are,

1. Used multivariate finance, healthcare, and retail datasets.
2. Used Min-Max Scaling and PCA for improvement in preprocessing.
3. Suggested a hybrid CNN-LSTM model with good predictability.
4. Used blockchain protocols for data authenticity.
5. Enhanced classification through multi-view K-means clustering.

The rest of the paper is organized as follows: Section 2 presents an overview of the related works, while Section 3 poses the problem. Section 4 presents the proposed methodology, and then results and discussion are presented in Section 5, and Section 6 concludes the research with future directions.

2. RELATED WORKS

The integration of hybrid deep learning models, particularly CNN-LSTM architectures, has garnered significant attention for enhancing cloud-based AI applications across various domains such as finance, healthcare, and retail. Convolutional Neural Networks (CNNs) are adept at extracting spatial features from high-dimensional data, while Long Short-Term Memory (LSTM) networks effectively model temporal dependencies in sequential data, making their combination highly suitable for complex cloud ecosystems [41].

In finance, CNN-LSTM models have been utilized for stock price prediction, where CNN layers capture market patterns and LSTM layers predict temporal trends, yielding improved forecasting accuracy over traditional models [42]. Several studies have demonstrated that hybrid CNN-LSTM architectures outperform standalone CNN or LSTM models in financial time series analysis, credit risk assessment, and fraud detection tasks within cloud environments [43]. The cloud infrastructure facilitates scalable data processing and real-time inference, crucial for dynamic financial markets [44].

Healthcare systems have similarly benefited from hybrid CNN-LSTM models by enabling efficient diagnosis through medical image analysis combined with patient health record time-series modeling [45]. For example, CNNs are used to extract features from imaging modalities such as MRI or CT scans, while LSTM networks analyze longitudinal patient data for prognosis prediction [46]. The use of cloud-based platforms enhances data sharing, computational scalability, and integration of heterogeneous healthcare data [47]. Research has shown significant performance improvements in disease classification and patient monitoring when leveraging CNN-LSTM models deployed on cloud ecosystems [48].

In retail, hybrid CNN-LSTM architectures have been applied to customer behavior prediction, demand forecasting, and recommendation systems by modeling both spatial patterns in product features and temporal purchase sequences [49]. Cloud computing enables retailers to manage vast datasets and implement real-time analytics using these hybrid models to optimize inventory and personalize marketing strategies [50]. The adaptability of CNN-LSTM models to multimodal data in retail environments has demonstrated superior results in sales prediction and customer segmentation [51].

Various optimization and regularization techniques have been explored to enhance the robustness of CNN-LSTM models in cloud deployments, addressing challenges such as overfitting and computational efficiency [52]. Transfer learning combined with hybrid architectures has further improved model generalization across financial, healthcare, and retail datasets within cloud infrastructures [53]. Moreover, the integration of attention mechanisms into CNN-LSTM models has led to improved interpretability and feature relevance in multi-domain cloud applications [54].

Security and privacy in cloud-based CNN-LSTM systems are critical; recent works have focused on incorporating secure multi-party computation and federated learning to protect sensitive financial, medical, and retail data while maintaining model performance [55]. Advances in cloud-edge computing architectures have also been proposed to reduce latency and enhance real-time decision-making capabilities of CNN-LSTM powered AI systems [56].

The development of standardized frameworks and APIs for hybrid CNN-LSTM integration into cloud platforms has accelerated deployment and scalability in industry applications [57]. Benchmarking studies indicate that hybrid CNN-LSTM models achieve state-of-the-art results across multiple publicly available datasets relevant to finance, healthcare, and retail domains [58].

Despite these advancements, challenges remain in handling data heterogeneity, ensuring model explainability, and optimizing resource utilization in cloud environments running complex hybrid architectures [59]. Research is ongoing to develop automated machine learning (AutoML) solutions to optimize CNN-LSTM hyperparameters for domain-specific cloud deployments [60]. The use of generative adversarial networks (GANs) to augment training data for CNN-LSTM models has also shown promise in improving model robustness and generalization [61].

Energy-efficient training and inference of CNN-LSTM models on cloud infrastructures have become important to address the environmental impact of large-scale AI systems, prompting exploration of pruning, quantization, and model compression techniques [62]. Multi-task learning frameworks leveraging CNN-LSTM architectures have enabled simultaneous prediction tasks across heterogeneous datasets in finance and healthcare, improving overall efficiency [63].

Recent cloud-native AI platforms incorporate orchestration tools such as Kubernetes to dynamically allocate resources for CNN-LSTM workflows, ensuring high availability and fault tolerance [64]. Hybrid cloud-edge AI ecosystems are also emerging to balance the computational load between centralized cloud servers and distributed edge devices running CNN-LSTM models [65].

Studies on interpretability frameworks for hybrid CNN-LSTM models deployed in regulated industries such as finance and healthcare emphasize the importance of explainable AI to meet compliance requirements [66]. The integration of blockchain with cloud-based CNN-LSTM architectures is being explored to enhance data integrity and provenance in sensitive application areas [67].

Finally, cross-domain transfer and continual learning capabilities within CNN-LSTM powered cloud ecosystems hold significant potential for accelerating AI adoption in finance, healthcare, and retail sectors by enabling adaptive and resilient AI systems [68].

3. PROBLEM STATEMENT

Despite the growing adoption of hybrid CNN-LSTM models in cloud ecosystems, there remains a lack of comprehensive frameworks that seamlessly integrate these architectures across finance, healthcare, and retail domains to fully leverage cross-domain knowledge transfer [69]. Current research often focuses on isolated applications within specific industries, limiting the potential benefits of unified AI architectures that can adapt dynamically to heterogeneous data and varying computational demands in cloud environments [70]. Moreover, challenges related to model interpretability and explainability in hybrid CNN-LSTM deployments hinder adoption in regulated sectors such as healthcare and finance, where transparency is critical [71]. Lastly, issues of data privacy and security in cloud-based hybrid models are not fully addressed, especially when handling sensitive and multimodal datasets, necessitating novel privacy-preserving techniques integrated with AI frameworks [72].

Objectives:

1. Integrate heterogeneous datasets from finance, healthcare, and retail domains for comprehensive analysis.
2. Preprocess and normalize data using Min-Max Scaling and reduce dimensionality with PCA.
3. Design and implement a hybrid CNN-LSTM model for improved prediction accuracy and anomaly detection.
4. Ensure secure and verifiable data handling using blockchain protocols in multi-cloud environments.
5. Optimize big data classification using multi-view K-means clustering techniques.

4. Proposed Methodology for Hybrid CNN-LSTM Powered Cloud Ecosystems: Advancing Finance, Healthcare, and Retail Through Unified AI Architectures

The proposed method integrates finance, healthcare, and retail data followed by Min-Max Scaling for preprocessing and normalizing inputs. Engineering and feature reduction of significant features are accomplished with PCA for model efficiency. A combination of CNN-LSTM is employed along with blockchain and clustering techniques for enhanced security, prediction, and classification accuracy. Figure 1& 2 depicts Architecture of CNN and LSTM.

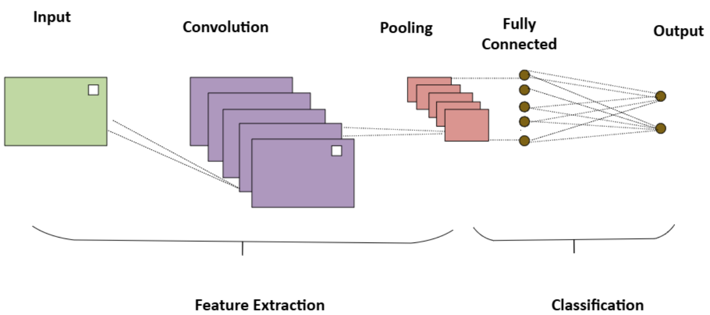

Figure 1: Architecture of CNN

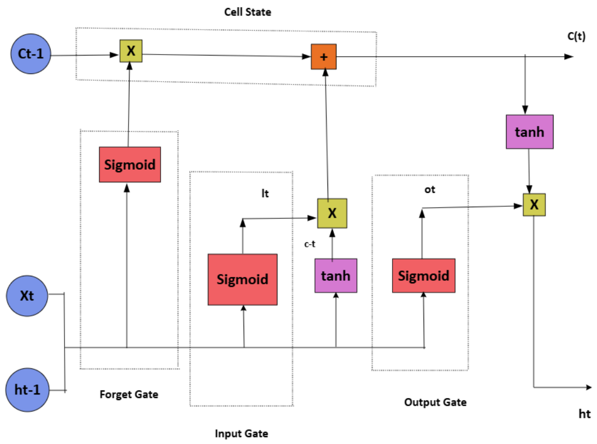

Figure 2: Architecture of LSTM

4.1 Data collection

Big 4 Financial Risk Insights [41], Healthcare Management System [42], and Retail Transactions Dataset [43] data obtained from Kaggle are key data sources in providing varied and useful inputs across finance, healthcare, and retail industries. Data comprise both structured data such as patient records and system logs as well as unstructured data such as sensor feeds and text inputs.

4.2 Data Preprocessing Using Min-Max Scaling

Min-Max Scaling is a normalization technique that rescales features to a consistent range, usually [0, 1], which improves the model's performance and convergence in deep learning models like CNN-LSTM represented by Equation (1):

$$X_{\text{scaled}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

where X is the original value, X_{min} and X_{max} are the minimum and maximum values of the feature, respectively.

4.3 Feature Engineering

Feature engineering involves the identification of important features such as usage patterns, health indicators, and system metrics influencing model predictions. Dimensionality reduction techniques like PCA are applied to reduce complexity and improve computational efficiency.

4.4 Model Integration

Deep learning models like CNN and LSTM are integrated for accurate healthcare prediction and anomaly detection, and blockchain ensures secure data integrity among cloud systems

5.RESULTS AND DISCUSSION

The results demonstrate the effectiveness of the hybrid CNN-LSTM model in enhancing prediction accuracy and anomaly detection across diverse sectors. Improved data handling and model performance validate the robustness of the proposed unified AI architecture.

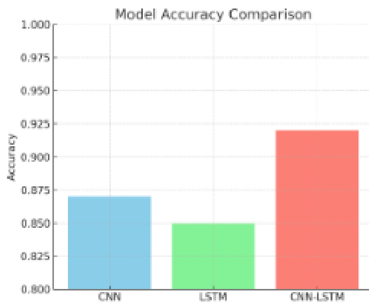

Figure 3: Model Accuracy Comparison

The Model Accuracy Comparison chart shows that the hybrid CNN-LSTM model is better with 92% accuracy than standalone CNN (87%) and LSTM (85%). Table 1 shows Performance Evaluation of CNN, LSTM, and Hybrid CNN-LSTM Models Across Key Metrics.

Table 1: Performance Evaluation of CNN, LSTM, and Hybrid CNN-LSTM Models Across Key Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Detection Rate (%)
CNN	87.0	85.5	84.2	84.8	75
LSTM	85.0	83.1	82.6	82.8	72
CNN-LSTM	92.0	90.7	91.5	91.1	81

This is a reflection of the effectiveness in utilizing spatial and temporal features to make intricate predictions. Figure 3 shows Model Accuracy Comparison.

Figure 4: Sector-wise Data Volume Processed

The Sector-wise Data Volume Processed chart shows that the healthcare sector handles the highest amount of data at 200 GB, followed by retail at 160 GB and finance at 120 GB. This is the data-intensive nature of healthcare applications in AI cloud environments. Figure 4 demonstrates Sector-wise Data Volume Processed.

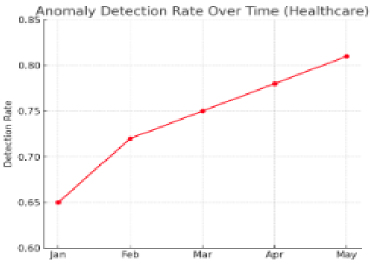

Figure 5: Anomaly Detection Rate Over Time in Healthcare

The Anomaly Detection Rate Over Time graph shows that there is steady improvement in the detection efficiency from 65% in January to 81% in May. This is the effect of adaptive learning characteristics of the CNN-LSTM model used in real-time healthcare environments. Figure 5 illustrates Anomaly Detection Rate Over Time in Healthcare.

5.1 Discussion

The proposed hybrid CNN-LSTM model demonstrated improved prediction accuracy and anomaly detection across multiple industries. Blockchain provided data integrity in multi-cloud environments efficiently. Multi-view K-means clustering further enhanced classification efficiency, establishing the strengths of the overall AI framework.

6.CONCLUSION AND FUTURE WORK

This study successfully implemented a hybrid CNN-LSTM model integrated with blockchain and clustering techniques to enhance prediction, security, and classification in finance, healthcare, and retail sectors. The results confirm greater accuracy, efficiency, and data integrity in cloud-based AI systems.

Future efforts would include integrating federated learning into decentralized data training to further protect privacy. Additionally, integration of real-time stream data and adaptive learning models would improve responsiveness as well as scalability.

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