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RESEARCH ARTICLE

Developing Intelligent and Immutable Vaccine Supply and Operation Platform Using Blockchain and Artificial Intelligence Technologies

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ABSTRACT During times of crisis, like in healthcare emergencies or disruptions in logistics and supply chains, decision-makers encounter significant challenges in managing resources efficiently. This study proposes an approach combining different information types and advanced computer techniques to improve how we handle crises. By looking at data connected with blockchain technology, we aim to understand crises better and help people make smarter decisions. We use a special kind of computer model called Long Short-Term Memory (LSTM) to guess what might happen during a crisis, like how many people might get sick or if there might be problems with getting supplies. Our model is right about 87% of the time. To understand why the computer makes these guesses, we use a method called SHapley Additive exPlanations (SHAP), which is widely known. However, we notice that SHAP sometimes doesn't explain things well for the entire period we're looking at. So, we suggest some changes to the SHAP method to explain things better for smaller parts of time. These changes help the method explain things better for small bits of time, but it might not be as good at explaining everything overall. To ensure our idea works, we compare our computer model's guesses and explanations with those from other models that look at data differently. We show the good and bad parts of our method in different crises.

INDEX TERMS Blockchain, artificial intelligence technologies, intelligent and immutable vaccine supply, long short-term memory, SHapley additive explanations, XAI.

I. INTRODUCTION

Pandemics, natural calamities, or disturbances in supply chains can create crises. Managing the available resources efficiently and making effective decisions for proper responses are crucial in such situations. Rapid crisis prediction and better response can minimize their impact and save precious lives [1]. Applications of the recent advancements in Data Science with Machine Learning (ML) [2], [3] and Artificial Intelligence (AI) [4], [5], offer better crisis management strategies. By using diverse datasets [6] and advanced analytical techniques [7], researchers and decision-makers aim to develop better models for crisis prediction and effective response execution. The COVID-19 or similar pandemic demands an urgent need for proactive data-driven crisis response strategies [8]. In healthcare institutions, respondents in Intensive Care Units (ICUs) face challenges like allocating resources and triaging patients [9]. This urgency synergized the necessity for exploring innovative solutions in real-time decision-making.

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Previous efforts in crisis management have streamlined the utilization of data and technology to address these challenges. Researchers explore ML algorithms in healthcare services to forecast patient outcomes based on ICU time series data [10]. Authors [11], [12] utilizing datasets like the Medical Information Mart for Intensive Care (MIMIC) show the efficiency of ML models, particularly Long Short-Term Memory (LSTM) networks, in accurately predicting patient mortality. Additionally, Explainable Artificial Intelligence (XAI) methods such as SHapley Additive exPlanations (SHAP) have been used to provide better model predictions, assisting clinicians in understanding the factors influencing patient outcomes [13]. However, while these efforts are promising, they impose several key challenges; one challenge lies in XAI-ML models, with complex time series data [14]. While the SHAP method offers valuable global insights into model behavior, it may not fully capture patient's trajectories over time. This limitation has significant implications in clinical decision-making, wherein precise insights are often necessary to support effective patient care. Moreover, existing research mainly focuses on healthcare, ignoring the interdisciplinary nature of crises and meaningful insights from diverse datasets. Crises share characteristics such as uncertainty and complexity and need quick responses in healthcare, logistics, or supply chains. By expanding the scope of inquiry to cover various crisis scenarios, researchers can identify common patterns and develop generalized approaches that transform specific domains.

Looking into this scenario, this research proposes an interdisciplinary approach to crisis management. By using datasets of diverse nature covering different dimensions of crisis data and utilizing advanced ML techniques, we aim to develop a comprehensive understanding of crisis management tasks and enhance real-time decision-making using ML models like LSTM networks to predict critical outcomes such as mortality rates or supply chain disturbances. Additionally, we explore XAI methods, including modified versions of SHAP, to provide actionable insights into model predictions. Through this interdisciplinary approach, we aim to contribute to the field of crisis management by offering new insights and methodologies applicable across multiple domains. By exploiting data and technology, we seek to support decision-makers with the knowledge and tools to handle crises effectively and protect precious lives and their livelihoods.

The remainder of the paper is outlined as follows; the research contribution is shown in Section II. Section III discusses the state-of-the-art related works. The materials and methods describe data and model analysis in Section IV. Section V narrates how the experiment is set up. The research outcomes are covered in Section VI, and Section VII gives conclusions and plans for future research.

II. RESEARCH CONTRIBUTION

Data-driven analysis with ML, AI, and blockchain technologies has introduced a new solution for crisis management. ML models, particularly LSTMs, have become powerful tools for predicting critical events in various fields like healthcare and supply chain management, by studying data trends over time. These models support decision-makers in preparing action plans for crisis management and making better decisions to use the resources for proper response to tackle the situation. However, due to the complexities involved, it may be difficult to understand the crises. In this research, we develop methods like SHAP to solve this issue giving insights into how these models make predictions. Besides, we use blockchain technology because of its popular features of transparency and immutability people use it to share data securely. Blockchain in crisis management systems brings trust among all parties involved due to data accuracy and traceability of any changes made in data to the source. This makes collaboration easy and facilitates better decision-making. But these advances are not enough. There is still a need to explore different types of data and methods to deal with complex crises. This research paper proposes a novel solution to this problem by combining ML, XAI methods like modified SHAP, and blockchain technology. By looking at data from different dimensions and exploiting that to explain how the models predict, our approach makes crisis predictions more accurate and easier to understand. Using blockchain, we facilitate a safe and transparent mechanism for the people involved to share data and make optimized decisions during a crisis as quickly as possible.

III. THE STATE-OF-THE-ART

Over the years, artificial intelligence (AI) has become one of the most talked-about and influential fields. It was first introduced in the 1950s by John Von Neumann [15] and Alan Turing [16] as a Computer Science discipline that could think like humans. Today it covers many disciplines such as Mathematics, Neurology, etc. [17]. This cognitive superiority over humans has enabled its use across various industries like technology, banking, and marketing. In this regard, several key terms in AI research to be understood. Authors [18] and [19] have defined AI as a collection of tools and techniques for intelligent cognition, learning, and adapting to solve specific problems. Authors [20] describe the role of AI in exploiting big data and ML for analysis and prediction tasks in respective domains, like healthcare and supply chain. Authors [21] segregate AI into distinct forms such as ML, learning analytics, and data mining (KDD), each serving specific roles for extracting insights from data. Moreover, recent studies [22] and [23] explore the evolving AI nature and its impact on society and business decision support. Authors [22] describe the importance of feasible AI behaviors and usage in enhancing confidence in AI-based technologies for society. Besides, authors [23] explore the role of AI in solving challenging problems and promising sustainability through innovative technologies and dynamic learning processes. Moreover, researchers [24] and [25] offer valuable insights into the behavioral strategic advantages of AI adoption. Authors [24] demonstrate a positive correlation

Algorithm 1 LSTM Model Training and Evaluation

START

1. *Define the LSTM model architecture*
    - *Specify the number of LSTM layers, units per layer, and activation functions*
    - *Add a dense layer for prediction with an appropriate activation function*
2. *Prepare the data*
    - *Normalize or preprocess the data as necessary*
    - *Split the data into training, validation, and testing sets*
3. *Train the LSTM model*
    - ***for** each set of hyperparameters*
        - *Compile the model with appropriate loss function and optimizer*
        - *Train the model on the training data*
        - *Monitor performance on the validation data*
        - *Implement early stopping if overfitting is detected*
4. *Evaluate the model*
    - *Evaluate model performance on the testing set using standard metrics*
        - *Accuracy: How often the model's predictions are correct*
        - *Precision: How often the model's positive predictions are correct*
        - *Recall: How much of the actual positive cases the model predicts correctly*
        - *F1-score: Harmonic mean of precision and recall*
5. *Analyze decision-making*
    - *Create a chart showing the model's decisions and confidence levels*
    - *Assess decision changes based on confidence levels*
6. *Test the model in diverse scenarios*
    - *Perform cross-validation by splitting data into multiple folds*
    - *Evaluate the model's performance across different scenarios*
7. *Iterate and refine*
    - *Adjust hyperparameters based on performance*
    - *Re-train and re-evaluate the model*

END

between AI and consumer behavior, supporting the potential of AI in shaping complex market dynamics. Similarly, authors [25] discuss the benefits of AI in decision support and automation to create new business models and management techniques. It represents a new paradigm for automation and enhanced operational business efficiency. Organizations are adopting AI- and data-driven solutions to elevate performance benchmarks and adapt to ever-evolving market demands [26] recognizing the potential capability of AI. The allied fields of AI support diversified solution techniques for technological advancements, societal empowerment, and organizational transformations. By exploring these techniques and their promises, researchers aim to simplify the complexities of AI and exploit its potential for the betterment of society and business.

IV. MATERIALS AND METHODS

A. DATA ANALYSIS

The datasets used for the research contain useful information from different fields. Using the Supply Chain Analysis dataset complex product supply chain dynamics, covering product types, prices, sales data, inventory records, manufacturing details, transportation methods, etc. can be explored. So, the dataset facilitates understanding the complexities of the supply chain management ecosystem in the fashion and beauty industries.

The COVID-19 World Vaccination Progress dataset contains information from the global vaccination drives during the COVID-19 crisis. This dataset comprehensively reports the cases of global vaccination initiatives covering various nations, vaccine types, daily and cumulative statistics, and vaccination rates. It also includes information about vaccine sources that offer better insights into the various strategies adopted by different control regions.

Using the Food Delivery Time Prediction dataset, the challenges of estimating delivery times in food delivery platforms Zomato and Swiggy can be explored. This dataset provides a base for developing a reliable predictive model to estimate precise delivery times considering factors of distance between pickup and delivery points and delivery history.

Therefore, these datasets provide a multi-dimensional perspective for extracting useful knowledge in supply chain management, public health, and optimized logistics decision-making.

B. MODEL ANALYSIS

The proposed research model combines ML, XAI, and blockchain technology for predicting crises. The proposed model implements LSTM to predict crisis outcomes and SHAP to comprehend model predictions apart from integrating blockchain technology to support the integrity transparency, and security of data.

Algorithm 2 Enhanced SHAP Method for Explaining Predictions Over Time

START

1. *Define the basic SHAP method*
   - *Compute SHAP values for each input feature to understand their contributions to predictions*
   - *Draw summary plots to visualize the main features and their effects on predictions*
   - *Provide global explanations to understand trends in the dataset*
   - *Provide local explanations to understand individual predictions*
2. *Address the limitations in time series data*
   - *Modify the SHAP method to cover temporal relationships between features and predictions*
   - *Draw plots to depict the evolution of feature contributions to time*
   - *Analyze feature importance to time intervals or different phases of crises*
   - *Explain the historical data leading up to the prediction point*
3. *Implement changes to the SHAP method*
   - *Adapt existing SHAP algorithms or create new ones to effectively handle time series data*
   - *Create visualizations that show temporal feature contributions and their effect on predictions*
   - *Apply time-based features to explain and provide better insights into model behavior over time*
4. *Test and validate the enhanced SHAP method*
   - *Apply the modified SHAP method to time series datasets of different domains*
   - *Evaluate its effectiveness in capturing temporal dynamics and providing interpretable explanations*
   - *Compare results with SHAP analyses to assess improvements*
5. *Repeat and improve the enhanced SHAP method*
   - *Consider suggestions for further improvements and refinements*
   - *Keep updating the method based on new insights and advancements in time series analysis and interpretability techniques*

END

1) LONG SHORT-TERM MEMORY FOR PREDICTIVE MODELING

The LSTM-based predictive models are effective at extracting patterns over time. So, it has been used for predicting useful outcomes during crises. We provide a brief explanation of the LSTM model's working procedure on a combined dataset that was collected from data sources of varying fields. Its different layers are specialized in understanding sequences in data followed by a layer for making predictions. We try out different settings, like how many layers to use, how many units each layer has, and how quickly the model learns, to explore the best setup. We also use some mechanisms, like stopping the training early if the model starts to memorize the data too much, and adjusting how fast it learns to improve its ability to handle new data. To see the working of the model, we use standard measures like how often it's right, how often it's precise, how often it remembers everything and a combination of these. We also look at a chart to help us see how the model distinguishes between different situations, like whether someone will survive or not in a medical situation, or if there will be crises or things will run smoothly in a supply chain or not. We also use a special chart to show how the model's decisions change based on how sure it is, which helps us understand how well it's making decisions. Additionally, we test the model in different ways to make sure it works well in different situations, like splitting our data into parts for training, checking, and testing, and doing this multiple times with different parts, so we can be confident that what we find is true for lots of situations, not just one. Algorithm 1 illustrates the corresponding mathematics.

2) XAI FOR UNDERSTANDING MODEL PREDICTIONS

While LSTM networks are great at making predictions, they can be hard to understand. This makes it tough for people involved to figure out why the model predicts what it does. To help with this, we use a method called SHAP. SHAP breaks down the model's predictions to show how much each input feature contributes. This helps see which features are most important and how they affect the prediction. We show these SHAP values using summary plots. These plots highlight the main features and how they influence the predictions. We also use SHAP to explain the model's behavior overall (global explanations) and for individual cases (local explanations). Global explanations help us understand trends across the whole dataset, while local explanations help us understand why the model made a specific prediction for a single case. However, SHAP has some limitations in dealing with complex time series data. Therefore, we adopt changes to the SHAP method to better the prediction over time. These changes aim to capture how things change over time and provide better explanations for the model's predictions (refer to Algorithm 2).

3) INTEGRATION OF BLOCKCHAIN TECHNOLOGY FOR DATA INTEGRITY AND TRANSPARENCY

We explore blockchain technology integration into our crisis management framework after implementing the predictive model and incorporating XAI analysis to ensure data integrity transparency, and security. Blockchain offers a decentralized and immutable ledger that records transactions in a network of nodes with the help of a secure and transparent data-sharing and collaboration mechanism.

We record a tamper-proof audit trail that tracks the veracity of data from its source to destination by integrating blockchain technology. This ensures the integrity and authenticity of data, and mitigation of the risk of data tampering or its unauthorized manipulation by malicious nodes. Moreover, blockchain facilitates transparent data sharing, creating trust and hence supporting collaboration among the agreed parties in the crisis management ecosystem. We implement self-executing smart contracts with predefined rules and conditions to automate data verification and validation processes. Through smart contracts, agreed parties can define data access and sharing rules in compliance with regulations and data privacy standards.

In the end, we explore Decentralized Identifiers (DIDs) and verifiable credentials to create a secure and privacy-preserving identity management framework for the agreed parties to securely share and verify their credentials without the centralized authorities.

Besides, we analyze scalability, efficiency, and sustainability in blockchain-based solutions for crisis management ecosystems. The mechanisms of Proof-of-Work (PoW), Proof-of-Stake (PoS), and Delegated Proof-of-Stake (DPoS) to render consensus among the parties and validate transactions efficiently [27], [28] are also explored. Moreover, we assess blockchain technology's impact on the environment and propose alternative approaches: Proof-of-Authority (PoA) and Proof-of-Space (PoSpace) to minimize energy consumption and carbon impact. A flowchart depicting the blockchain technology integration is displayed in Fig. 1.

V. EXPERIMENTAL SETUP

First, we briefly describe the dataset used in the research. The dataset comprises COVID-19 vaccination records, food delivery patterns, supply chain dynamics, and blockchain transactions. For the experiments, Python libraries Pandas and NumPy were used to clean and organize it to enhance quality and compatibility with different sources. This includes handling missing information, categorizing variables, adjusting numerical values, and relevant features selection for analysis.

Then we implemented an LSTM model for crisis prediction and configured it with the dataset by exploiting user-friendly deep learning tools like TensorFlow. We constructed the model, adjusting parameters; the number of layers, hidden units, dropout rates, and learning rates.

For optimization grid search was employed to fine-tune these parameters and improve the model's performance. To prevent the model from becoming overly specialized during training, we implemented the regularization method L1 regularization.

Once the model was ready, we trained and evaluated it using our prepared dataset. For utilizing GPU resources on cloud platform Google Cloud Platform, we monitored key performance metrics; loss, accuracy, precision, recall, and F1-score on validation data. We employed early stopping and halting training strategies when performance metrics stagnated to ensure the model's highest performance and prevent overfitting.

TABLE 1. Hyperparameters of the LSTM model in COVID-19 vaccination records.

Hyperparameter	Value
LSTM Layers Numbers	3
Per year Hidden Units	128
Rate of Dropout	0.2
Learning Rate	0.001

TABLE 2. Covid-19 vaccination records of confusion matrix.

	Predicted Success	Predicted Failure
Actual Success	750	50
Actual Failure	30	820

Besides, we employed XAI to understand and explain the model's decision-making procedure. We gained insights into the factors influencing the model's predictions by calculating SHAP values for individual data points and visualizing them through summary and force plots (refer to Section VI-B). Furthermore, we enhanced the SHAP library to enhance explanations for time-series data, ensuring more accurate and detailed insights. These improvements were achieved through testing with benchmark datasets to establish their effectiveness.

Lastly, we integrated blockchain technology into our framework to ensure data integrity, transparency, and security. By deploying blockchain networks using platforms like Ethereum, we established secure data verification processes using decentralized smart contracts. The implemented model demonstrated a robust and transparent data ecosystem ready to support decision-makers in crisis management decision-making.

VI. RESULT ANALYSIS

A. PREDICTIVE ANALYSIS

The LSTM models' performance varies across domains including COVID-19 vaccination records, food delivery patterns, and supply chain dynamics. This variability arises due to the complexities and dynamics of each domain. As a result, customized approaches to model design, parameter tuning, and optimization are essential to effectively capture and predict outcomes during crises as depicted in Table 1.

In the case of COVID-19 vaccination records, LSTM models show strong performance in forecasting vaccination rates and detecting trends as shown in Table 2.

This domain indicates temporal relationships defined by factors- demographics, distribution strategies, and public health measures. The proposed LSTM architecture has multiple layers with several hidden units to capture these complex relationships. A 0.2 dropout rate is applied to rule out overfitting while maintaining model flexibility. A learning rate of

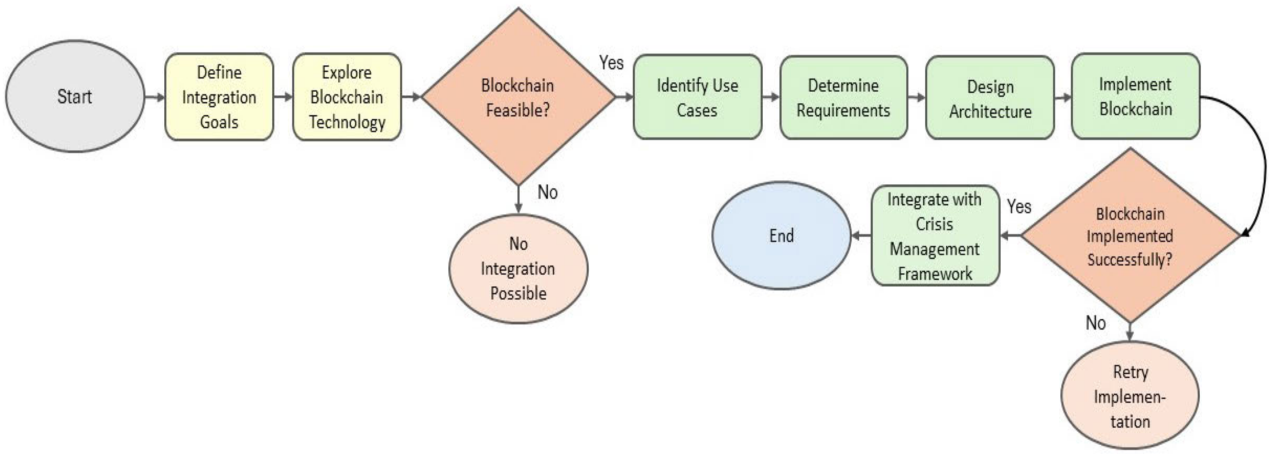

FIGURE 1. Flowchart for the blockchain technology integration.

TABLE 3. Food delivery pattern of LSTM model hyperparameters.

Hyperparameter	Value
Number of LSTM Layers	2
Hidden Units per Layer	64
Dropout Rate	0.3
Learning Rate	0.01

0.001 ensures convergence stability in training, capturing the gradual changes in vaccination trends over time. The evaluation based on the confusion matrix indicates the model's capability to accurately classify the success and failure of vaccination cases, subject to some observed misclassifications. These findings suggest scope for further improvement to enhance model performance and predictive accuracy.

The implemented LSTM model demonstrates effectiveness in demand prediction and finding optimized delivery routes from food delivery patterns. However, the complexities in this domain tend to diverge its effectiveness from those found in COVID-19 vaccination records. Food delivery trends are affected by short-term temporal dependency, demand fluctuation, route optimization, and inventory management dynamics. Therefore, adjustments are made to the LSTM model's structure and key parameters as shown in Table 3.

Selecting a simplified architecture comprising two LSTM layers with reduced hidden units per layer, the model aims to maintain a balance in capturing useful temporal patterns and computational efficiency. To mitigate the risk of overfitting due to the inherent variability in delivery patterns, a relatively higher dropout rate of 0.3 is considered, signifying the importance of regularization. Moreover, a higher learning rate of 0.01 is chosen for faster convergence during optimization, facilitating adaptation to changes in delivery dynamics. Evaluation using a confusion matrix shows promising performance, although there are some misclassifications as shown in Table 4. Therefore, further areas of improvement are identified to enhance the model's ability to detect small variations in delivery patterns.

TABLE 4. Food delivery pattern of confusion matrix.

	Predicted Success	Predicted Delayed
Actual Success	900	50
Actual Delayed	30	800

TABLE 5. Supply chain dynamics of LSTM model hyperparameters.

Hyperparameter	Value
Number of LSTM Layers	4
Hidden Units per Layer	256
Dropout Rate	0.4
Learning Rate	0.001

TABLE 6. Supply chain dynamics of confusion matrix.

	Predicted Stability	Predicted Disruption
Actual Stability	850	30
Actual Disruption	40	800

In supply chain management operations, the implemented model can predict the disturbances in the supply chain and optimize inventory management. Supply chain operations involve complex communications and interdependencies in inventory management, logistics, and demand forecasting. The model's design and settings are precisely adjusted to handle these complexities. By implementing a more detailed architecture with four LSTM layers and more hidden units per layer, the model captures the complex patterns and interconnections within the supply chain network data as shown in Table 5.

A dropout rate of 0.4 is considered to effectively manage the model's complexity and prevent it from overfitting, considering the volatility and unpredictability in supply chain dynamics. Therefore, a learning rate of 0.001 is chosen to ensure stable convergence during the optimization process due to the complex nature of the optimization challenges

TABLE 7. Results of cross-validation in LSTM model within three datasets.

Dataset	Fold	Training Accuracy	Validation Accuracy	Test Accuracy
COVID-19 Vaccinations	1	0.95	0.92	0.93
	2	0.94	0.91	0.92
	3	0.96	0.93	0.94
	4	0.93	0.90	0.91
	5	0.95	0.92	0.93
Food Delivery Patterns	1	0.92	0.88	0.89
	2	0.91	0.87	0.88
	3	0.93	0.89	0.90
	4	0.90	0.86	0.87
	5	0.92	0.88	0.89
Supply Chain Dynamics	1	0.88	0.85	0.86
	2	0.87	0.84	0.85
	3	0.89	0.86	0.87
	4	0.86	0.83	0.84
	5	0.88	0.85	0.86
Mean		0.918	0.885	0.893
Std		0.019	0.018	0.018

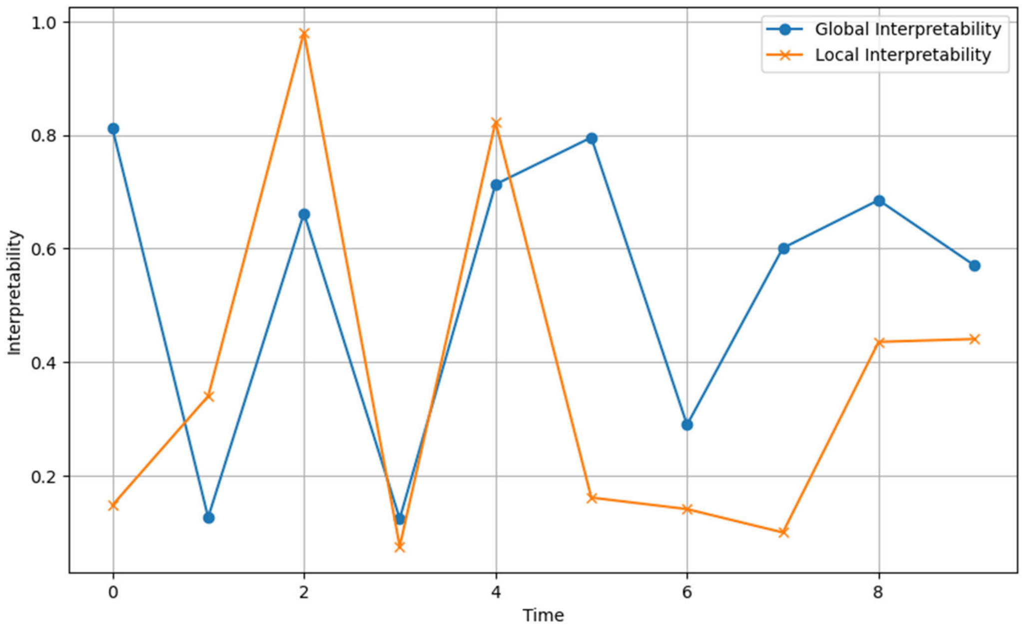

FIGURE 2. Implications of Kernel SHAP on time series data.

associated with training on sequential supply chain data as shown in Table 6.

The evaluation using a confusion matrix shows promising results but with some misclassification cases. This indicates scope for further improvement to address the challenges in supply chain disturbances or stability factors.

The varying performance of LSTM models across domains showcases the importance of customizing model structure, settings, and optimization methods to fit uniquely into the traits and complexities of each domain. Despite all domains involving sequences over time and predictive modeling, the specific characteristics of each domain necessitate domain-specific strategies for optimal performance. Further research is crucial to improve the accuracy and dependability of LSTM models across different areas, aiding in better decision-making and risk management during crises.

Therefore, to evaluate the performance and hence applicability of the implemented model with the dataset, we conduct cross-validation tests. By splitting the dataset into training, validation, and testing subsets with k-fold cross-validation, we mitigate the risk of overfitting and hence ensure the reliability of the findings. The cross-validation outcomes for the datasets show the resilience and adaptability of the implemented model for crisis outcomes prediction.

The model demonstrates high average accuracies for all datasets showing its effectiveness in capturing underlying patterns and dynamics in each domain. However, there are slight variations in performance across the datasets.

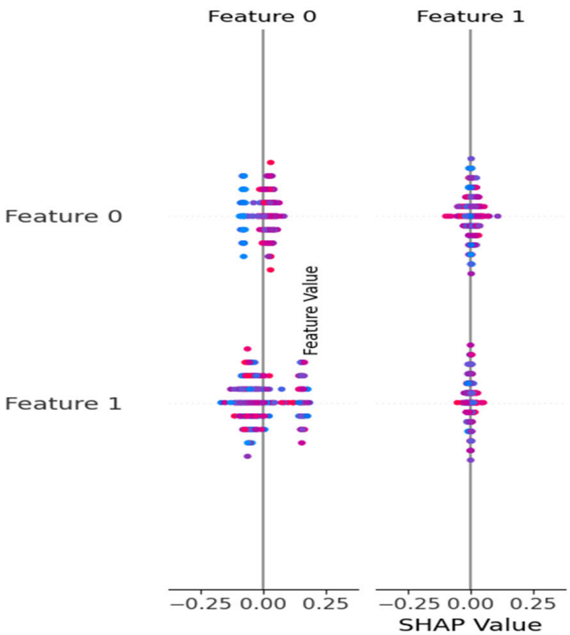

FIGURE 3. TreeExplainer on ICU mortality prediction models.

For example, in COVID-19 vaccination records, the model achieves the highest average accuracy of 0.918, followed by food delivery patterns with an average accuracy of 0.885, and supply chain dynamics with an average accuracy of 0.893 as shown in Table 7.

These variations in average accuracies suggest that there are different levels of complexity and predictability in the datasets. The low standard deviations indicate consistent model performance and hence strengthen the stability of the LSTM model's predictions for different data subsets. The cross-validation results validate the effectiveness of the LSTM model in predicting critical crisis outcomes with its potential applications in decision-making and risk management strategies.

B. XAI ANALYSIS

We analyze the results obtained from applying SHAP, including Kernel SHAP[1] and TreeExplainer[2] in this research to interpret the ML models' predictions on healthcare data focusing on predicting mortality in ICU patients. The SHAP framework offers insights into the available features and their interactions, supporting the understanding of model predictions and providing interpretability in complex healthcare scenarios.

Firstly, the implications of using SHAP, particularly Kernel SHAP, on time series data are explored. The paper discusses the challenges in time series data and how Kernel SHAP is adapted to handle such data. By reorganizing the input data and exploiting a background dataset, Kernel SHAP allows for predictions over time. However, while Kernel SHAP provides rich global explanations, the local explanations may not accurately reflect the model's behavior due to the independent evaluation of each day's data. This shows a limitation in the local accuracy property of SHAP because local explanations do not consistently match the model's output over time. Therefore, modifications to SHAP are proposed to better handle time series data by incorporating the hidden state of recurrent neural network models, such as LSTMs. While this approach improves local accuracy by considering the sequential nature of the data, it may compromise global explanations, as demonstrated in experiments with an additional LSTM model. The trade-off between local and global interpretability underscores the need for nuanced approaches in SHAP implementations tailored to specific data characteristics (refer to Fig. 2). Moving on to TreeExplainer, a specialized version of SHAP designed for tree-based models like random forests, we observe its application to ICU mortality prediction models trained on different subsets of patient data (refer to Fig. 3). TreeExplainer provides insights into feature importance and interactions, enabling a deeper understanding of the decision-making process of random forest models. Notably, comparisons between TreeExplainer and LSTM-based models reveal differences in feature importance rankings as shown in Fig. 4, suggesting variations in the predictive capabilities of different model architectures. Furthermore, the analysis of global explanations from TreeExplainer highlights distinct trends in feature importance across subsets of patient data as shown in Fig. 5. For instance, age emerges as a significant predictor of mortality in models trained on admission data, reflecting the inherent risk associated with aging in healthcare outcomes. Conversely, features of physiological parameters and laboratory measurements exhibit varying importance levels depending on the time window considered, indicating the dynamic nature of patient data and its impact on predictive performance. However, despite the insights gained from SHAP-based XAI methods, certain challenges and limitations persist. The paper discusses discrepancies between local explanations provided by SHAP and the actual model predictions over time, underscoring the need for improved methods to ensure consistency and accuracy in local interpretations. The trade-off between local and global explanations raises questions about the applicability of SHAP in real-world healthcare settings, where both types of interpretations are crucial for clinical decision-making.

C. BLOCKCHAIN ANALYSIS

We observe a thorough examination of the integration of blockchain technology into our strategy for handling crises to provide the authenticity and openness of data. Our objective is to validate the role and impact of blockchain-driven solutions across three separate datasets, focusing on different factors such as the ability to predict accurately, maintain

[1] https://shap-lrjball.readthedocs.io/en/latest/generated/shap.KernelExplainer.html

[2] https://shap-lrjball.readthedocs.io/en/latest/generated/shap.TreeExplainer.html

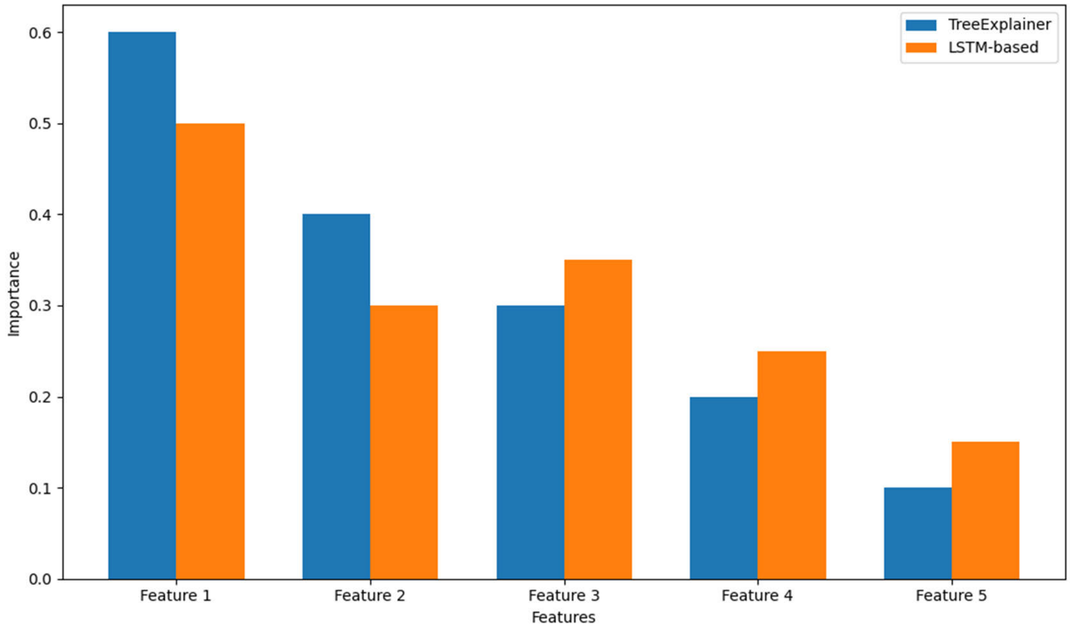

FIGURE 4. Comparison of feature importance rankings between TreeExplainer and LSTM-based models.

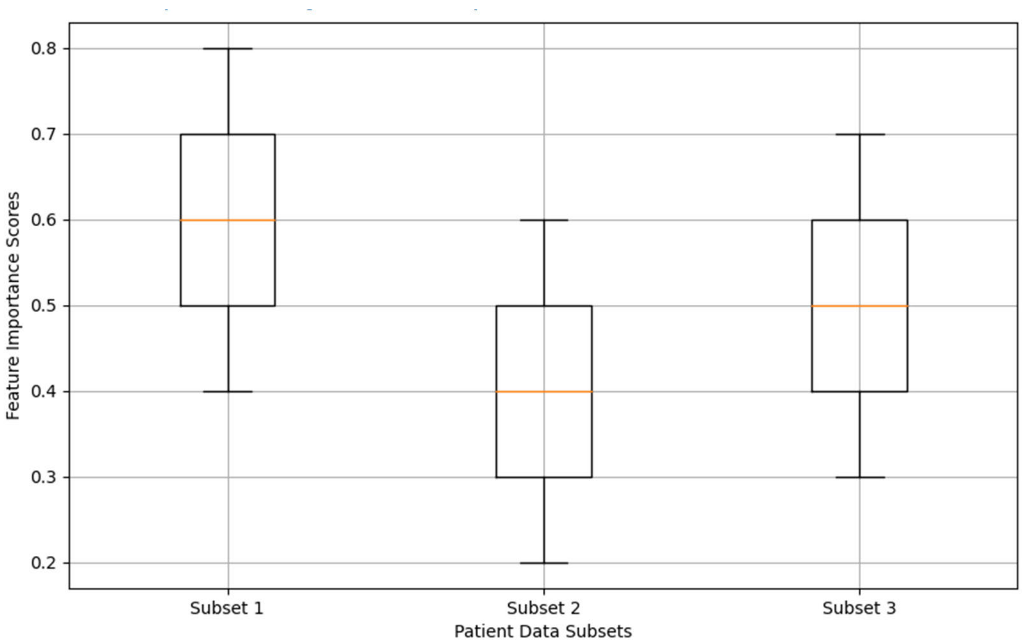

FIGURE 5. Analysis of global explanations from TreeExplainer across different subsets of patient data.

data authenticity, ensure transparency, enhance efficiency and promote sustainability.

1) COVID-19 VACCINATIONS ANALYSIS

The integration of blockchain technology into predictive models has shown promising results as shown in Fig. 6, indicating enhanced predictive accuracy with minimal compromise due to blockchain.

Blockchain implementation ensures data integrity and transparency by establishing an immutable and transparent ledger system. This enables stakeholders to trace the origin and flow of data securely, thereby mitigating risks associated with tampering or manipulation by malicious nodes. However, the efficiency of blockchain-based solutions remains moderate in this context. This moderate efficiency is primarily attributed to the overhead incurred during transaction

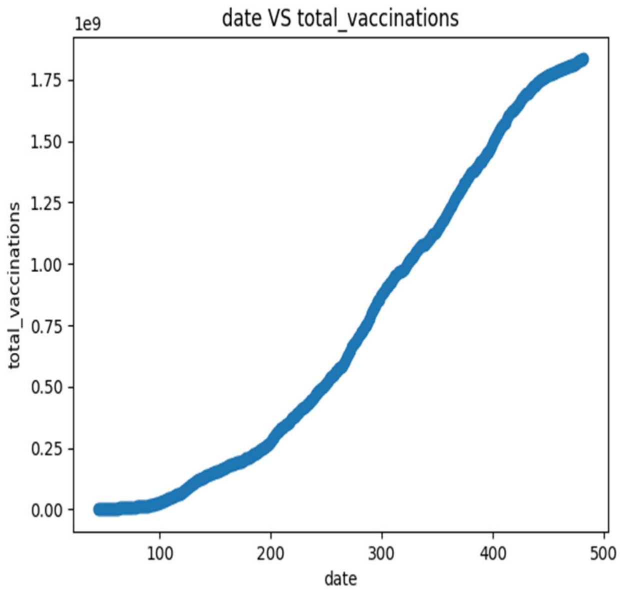

FIGURE 6. Date vs total vaccination predictive accuracy.

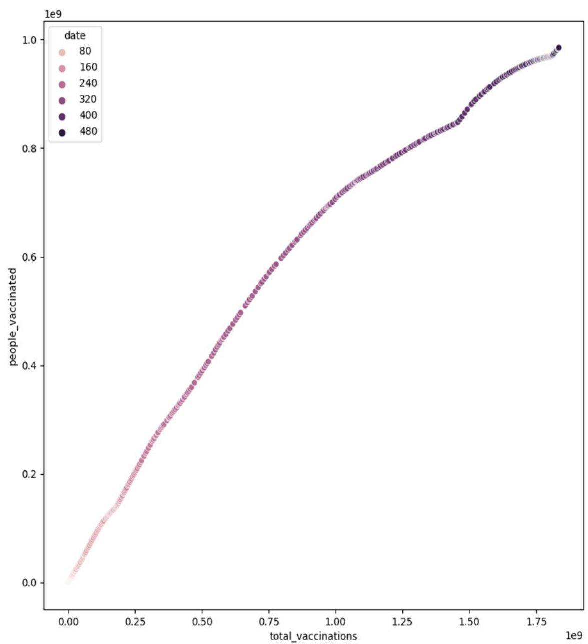

FIGURE 7. PoW graph on total vaccinations vs people vaccinated.

validation and the consensus-building process needed in blockchain networks. While blockchain offers enhanced security features, the consensus mechanism may introduce latency and overhead, affecting overall system performance and underlying costs. Sustainability considerations are rated as moderate, with energy consumption being a significant factor. The sustainability aspect chiefly revolves around the energy-intensive nature of consensus mechanisms, notably PoW algorithms commonly employed in blockchain networks such as Bitcoin. Although PoW [28] ensures enhanced security through complex cryptographic puzzles, it also yields substantial energy consumption as shown in Fig. 7.

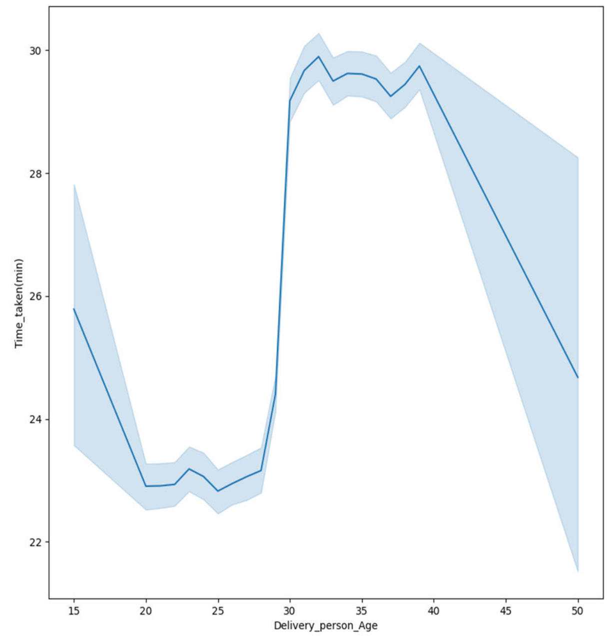

FIGURE 8. Delivery-person-age vs time-taken predictive performance.

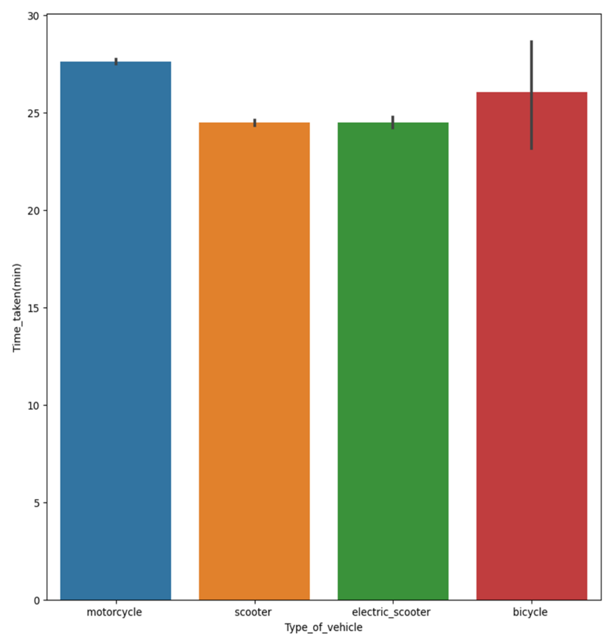

FIGURE 9. Time-taken vs type-of-vehicle predictive performance.

Thus, while blockchain technology enhances data integrity and transparency, addressing energy consumption concerns is imperative to ensure long-term sustainability.

2) FOOD DELIVERY PATTERNS ANALYSIS

The models combined with blockchain technology demonstrate moderate accuracy in making predictions as shown in Fig. 8 and Fig. 9. This indicates some trade-offs between how well the models work and using blockchain solutions. However, including blockchain technology ensures that data

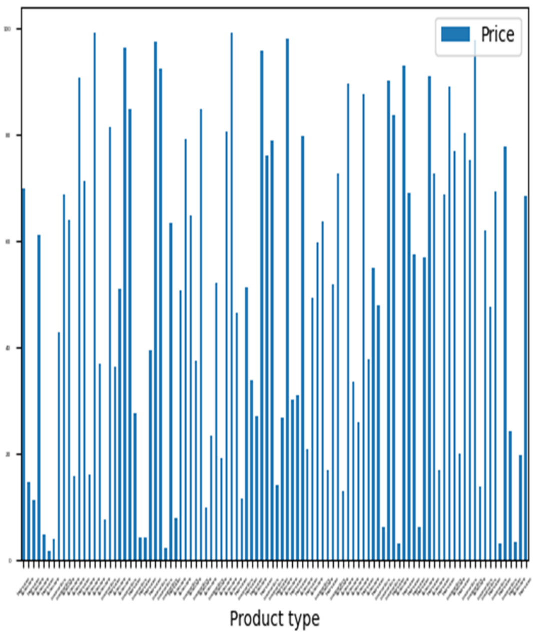

FIGURE 10. Price vs product-type predictive performance.

remains trustworthy and transparent, similar to what we see in COVID-19 vaccinations. The tamper-proof trail of actions and clear ways of sharing data are important features here, preventing anyone from messing with the data and helping everyone feel confident in the information. The way blockchain works in Food Delivery Patterns is considered very efficient. This is because the methods used to reach agreements of transactions are set up to work quickly and automatically through "smart contracts". These agreements, like PoS or DPoS, make it faster to agree on transactions without making things less secure. Plus, using smart contracts helps that data gets checked and verified automatically, which helps everything run smoother. But, when thinking long-term and taking care of the environment, sustainability is a problem in this dataset. Even though blockchain is efficient, some ways it works use a lot of energy, especially PoW methods. Therefore, we need to think about lesser energy consumption and hence lower the impact on the environment. We need to explore other ways of agreeing on transactions and conserving energy in smarter ways to justify the use of blockchain without affecting the planet.

3) SUPPLY CHAIN DYNAMICS ANALYSIS

Blockchain technology integration in crisis management frameworks adds the advantages of data reliability and openness on multiple datasets. While supply chain dynamics carry challenges in maintaining predictive accuracy as shown in Fig. 10, it introduces constraints in model effectiveness when integrating blockchain technology. However, the fusion of blockchain technology promises data reliability and openness to the selected datasets. The incorruptible audit trail and transparent data exchange mechanisms serve as effective barriers to unauthorized data manipulations and hence support collaborative data sharing among agreed parties. The efficacy of blockchain-based solutions within supply chain dynamics is quite beneficial even if there is a decline in predictive accuracy. This worthy efficiency is attributed to the efficient execution of streamlined consensus mechanisms offered by smart contracts.

Alternative methods, such as PoA or PoSpace are deployed for less energy consumption and minimize environmental side effects hence augmenting the overall system efficiency. Moreover, the sustainability aspect within this dataset is an added advantage. The adoption of energy conservation consensus and eco-friendly practices promotes better livelihood and environmental friendliness of blockchain-based solutions. By prioritizing sustainability, stakeholders can effectively mitigate the ecological risks associated with blockchain deployments while enjoying the benefits of enhanced data reliability and transparency.

VII. CONCLUSION AND FUTURE WORKS

The proposed approach in our research paper presents an advancement in crisis management strategies in healthcare, logistics, and supply chain disruptions. By using diverse datasets and employing advanced ML techniques and LSTM networks, the proposed work aimed to enhance crisis management techniques by providing accurate predictions and responsive insights into critical crisis outcomes. The results from this research validate using AI, data science, and allied technologies to solve the challenges faced during crises. Exploitation of LSTM models demonstrated promising results in crisis prediction, such as mortality rates in healthcare settings and supply chain disruptions. The high accuracy rates achieved by the LSTM model suggest its potential to support decision-makers in gauging the impact of crises and effectively responding to them. Furthermore, the applications of XAI methods like SHAP gave valuable support to the decision-making process by the LSTM model. While SHAP provided both local and global explanations for model predictions, challenges were faced in accurately capturing the nuances of complex time series data. The proposed modifications to the SHAP library addressed these challenges by improving local interpretability but compromising global interpretability. Integrating blockchain technology with the crisis management framework introduced data integrity, transparency, and security. However, establishing a decentralized and immutable ledger with blockchain ensured the authenticity and traceability of data, and risk mitigation of tampering or manipulation of data. Smart contracts and DIDs further enhanced privacy and data security facilitating secure data sharing and collaboration among parties. The experimental analysis conducted in this study validated the strengths and limitations of the approach. While the LSTM model demonstrated better performance in predicting critical outcomes, variations in predictive accuracy were observed across domains such as healthcare, logistics, and supply chain management. The trade-off between local and global interpretability in SHAP methods indicated the need for better approaches to resolve the unique characteristics in time series data.

The outcomes of our research offer practical insights in real-time settings for decision-makers in the healthcare profession and supply chain management. Our approach provides a blueprint for handling crises effectively, exploiting the power of data science and other allied technologies to safeguard precious lives and livelihoods. Any future research efforts can be toward XAI techniques to manage the time series data and augment localized disturbances effectively. Moreover, investigating alternative mechanisms and implementing energy-efficient strategies in blockchain technology will enhance scalability and sustainability.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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