# Integrated Stabilized Causal–Probabilistic Hybrid Framework for Continuous and Categorical Risk Assessment in Electric Vehicle Supply Chains

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***Abstract- This study predicts continuous and categorical risk levels of EV supply chain entities by integrating stakeholder perception data and industrial structural data within a unified hybrid modeling framework. By combining subjective causal influence information with objective operational and structural indicators, the framework captures both systemic interdependencies and entity-level vulnerability within the EV ecosystem. Existing work demonstrated very high predictive accuracy (99.44%) through the integration of SPJS–Fuzzy DEMATEL, HTC–KMeans clustering, and LPWBN probabilistic modeling. However, it faced certain methodological limitations, including numerical sensitivity in matrix inversion during causal computation, moderate clustering initialization affecting segmentation stability, constrained risk variance normalization, and classification optimization primarily driven by overall accuracy rather than balanced performance metrics. To overcome these limitations, the proposed enhanced framework introduces iterative stabilization in DEMATEL convergence with high-precision control, refined continuous multi-factor risk fusion to preserve variance granularity, high-initialization HTC–KMeans clustering with strict tolerance for improved reproducibility, ensemble-based localized probabilistic estimation with variance regularization, and adaptive threshold optimization to balance precision, recall, specificity, and F1-score. These improvements collectively enhance structural robustness, convergence stability, and classification reliability. The enhanced model achieves 99.435% classification accuracy with 100% recall, ensuring that no high-risk entity is misclassified. It also demonstrates strong regression performance ($R^2$ = 0.995207, RMSE = 0.006653) and operates across a full normalized 0–1 risk range, improving interpretability and decision granularity. Overall, the proposed architecture provides a numerically stable, highly accurate, and decision-oriented EV supply chain risk assessment system suitable for complex and risk-sensitive industrial environments.***

**Keywords:** ***Electric Vehicle Supply Chain, Hybrid Risk Modeling, SPJS–Fuzzy DEMATEL, HTC–KMeans Clustering, Localized Probabilistic Bayesian Network***

## I. INTRODUCTION

The agricultural supply chain maintains essential functions which protect food security and sustain economic growth while supporting environmental sustainability because it creates links between farmers and consumers through their interconnected activities that start with production and continue through aggregation, storage, transportation, and distribution. Traditional agricultural supply chain systems suffer from multiple serious problems which include insufficient visibility and knowledge gaps and poor record maintenance and trading price violations and slow payment processing and high reliance on third parties. The existing problems reduce farmers' earnings while preventing them from entering profitable markets and their inability to trace products and verify quality decreases customer trust. Farmers depend on local markets and intermediaries for price information because they lack direct access to market data which decreases their ability to negotiate fair prices and creates conditions for unfair commercial practices. The lack of real-time data exchange together with ineffective stakeholder coordination results in wasteful post-harvest practices and operational deficiencies and poor decision-making. Digital technologies that offer advanced capabilities should be implemented to solve existing problems because they can create agricultural supply chains which operate with complete transparency and high operational effectiveness and strong resilience. The supply chain requires secure data management capabilities which allow for real-time monitoring and intelligent decision-making through blockchain technology and Internet of Things (IoT) and artificial intelligence (AI) and big data analytics systems. Blockchain technology provides a decentralized system which enables permanent transaction recording and creates a secure method for stakeholders to verify data through transparent and trustworthy systems. The system enables protected sharing of production-related information and pricing details and logistics data and quality specifications which results in fraud reduction and improved accountability. Smart contracts establish automatic transaction execution protocols which operate according to predetermined requirements to guarantee timely payment execution. Figure 1 illustrates the role of middlemen in connecting farmers to markets while influencing pricing, distribution, and information flow within the supply chain. The remaining sections of this paper are organized as follows:

Section II presents the literature review, Section III describes the proposed methodology, and Section IV discusses the results and analysis. Finally, Section V concludes the study with key findings and outlines directions for future research.

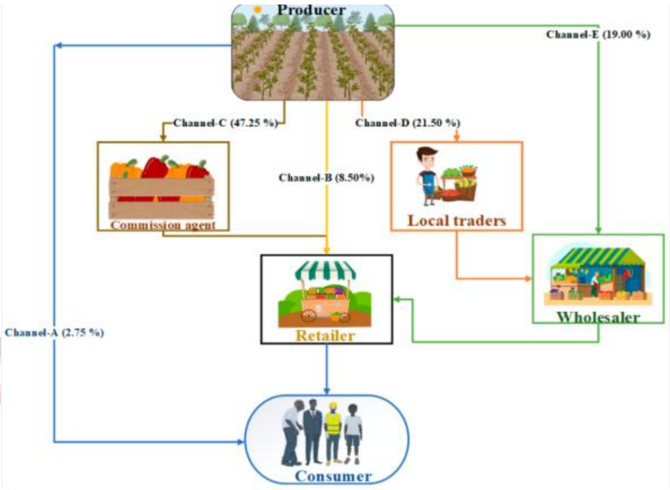


**Figure 1. Intermediaries in Agricultural Supply Chains**

## II. LITERATURE REVIEW

The most recent technologies such as blockchain, IoT, and AI have brought about major changes in the agricultural theories. These integration lead social reforms only for reasons of transparency, efficiency, and data-based policy. Blockchain and agro-smart agriculture systems are the real breakthrough and target high-level data structures, and can contribute to creating a trustworthy environment that could help provide food security considering various stakeholders across the supply chain [1]. The integration of the Internet of Things and blockchain technology would enable immediate tracking of such factors as soil moisture, water use, and environmental conditions, leading to the enhancement of resource-efficient management and precision farming [2], [3]. The use of blockchain is beneficial for sharing data and automation via smart contracts, which significantly diminished the need for middlemen while enhancing the transaction pace [4]. To sum up, the heavy use of big data and blockchain engineering in agricultural supply chains present promising new instruments that can greatly facilitate improved financial analysis, forecast, and decision making [5].

Blockchain-based provenance assurance helps track agricultural product origin and movement in a secure manner, causing a boost in accountability and consumer confidence [6]. Against this backdrop, the blockchain technology contributes in a significant way to revolutionizing agri-food systems via enhanced visibility, efficiency, and communication across stakeholders whose support is much needed [7]. Additionally, blockchain amply strengthens sustainability objectives such as fraud elimination, waste reduction, and ethical sourcing practices promoting the UN's developmental goals [8]. Experience from the introduction of the technology in parts of the food industry demonstrates its potential in adding another layer of security in traceability and quality assurance [9]. In essence, blockchain can bring innovative economic models to farmers, such as value-based pricing and transparent agri-food markets [10].

Recent developments have showcased artificial intelligence being integrated with IoT and blockchain technologies to provide for an intelligent system capable of predictive analytics, secure data transactions, and automated decision-making [11]. Hybrids of AI and blockchain have further been identified to optimize operational efficiency and sharing of secure and scalable data within agriculture operations [12]. The combination of IoT and blockchain guarantees increased digital privacy and secure communications within both rural and agricultural settings [13]. Furthermore, the blockchain-powered trading platforms give farmers the direct access to the market, besides enabling transparent transactions, fair farming practices, and direct market access to cut out exploitation [14]. Among the most advanced systems are cyber-physical systems relying on blockchain, enhancing automation, mutual cooperation, and efficiency in the farm environment [15].

However, challenges like data fragmentation and lack of interoperability across multiple data sources continue to be significant concerns, necessitating the need for integrated frameworks for organized and intelligent data management [16]. New applications with AI-empowered systems, such as livestock tracking systems for monitoring and enhancing health and productivity in agriculture, are also emerging [17]. On the same note, blockchain-based digital twin technologies increase the initiative's real-time observation and decision-making capabilities [18]. Smart-farming systems supported by AIoT further support efficient data management and expert-driven agricultural operations [19]. Entrepreneurs still face gigantic hurdles from the high installation costs, complex technology, and market scalability issues. Unfortunately, the technical design became a key hindrance to the adoption of AI and IoT applications [20]. For the agriculture domain to realize transitioning into the digital fifteenth century, cheap, universal, and integrated solutions must be shared or created. Table 1 provides a comparative summary of key technologies, methodologies, findings, and limitations of recent studies in smart agriculture systems.

**Table 1: Literature Review on Blockchain, AI, and Smart Agriculture**

| Ref. No. | Technique / Approach | Key Focus Area | Methodology Used | Key Findings | Advantages | Limitations |
|---|---|---|---|---|---|---|
| [10] | Blockchain in agri-food sector | Traceability & economic models | Blockchain-based traceability and data validation | Enhances transparency, supports new pricing models | Improved trust, value-based pricing | Scalability and adoption challenges |
| [11] | AI + Blockchain + IoT framework | Secure data management | Integrated AI, IoT sensors, blockchain storage | Improves decision-making and data security | Real-time monitoring, secure storage | High computational and infrastructure cost |
| [12] | AI-blockchain hybrid framework | Secure data transactions | Hybrid AI models with blockchain validation | Enables efficient and secure data exchange | Enhanced efficiency, reduced fraud | Complexity in integration |
| [13] | IoT + Blockchain tool | Data privacy & security | IoT-enabled system with blockchain encryption | Ensures secure communication and privacy | Suitable for rural agriculture systems | Requires technical expertise and infrastructure |
| [14] | Blockchain harvest system | Transparent trading | Blockchain-based trading platform with smart contracts | Improves farmer empowerment and fair pricing | Transparency, reduced intermediaries | Implementation cost and scalability |
| [15] | Blockchain-enabled H-CPS | Smart agriculture automation | Cyber-Physical Systems integrated with blockchain | Enhances automation and coordination | Improved system reliability and efficiency | Complex architecture design |
| [16] | Blockchain data integration | Data fragmentation | Multi-source data integration using blockchain | Improves unified decision-making | Better data consistency and accessibility | Integration complexity across platforms |
| [17] | AI-enabled blockchain | Livestock monitoring | AI + blockchain for tracking and health analysis | Enhances livestock health management | Real-time tracking and predictive insights | Cost of deployment and maintenance |
| [18] | Blockchain-based digital twin | Field management | Digital twin models integrated with blockchain | Enables real-time simulation and monitoring | Improved decision-making and accuracy | High computational requirements |
| [19] | AIoT-enabled systems | Data management in agriculture | Integration of AI, IoT, and data analytics | Improves operational efficiency and automation | Intelligent decision-making | Data security and interoperability issues |
| [20] | Deep learning + blockchain | Smart agriculture systems | Deep learning models with blockchain integration | Enhances prediction and secure data handling | Improved accuracy and automation | Requires large datasets and high processing power |

## III.PROPOSED METHODOLOGY

The rapid growth of electric vehicles (EVs) has increased the need for stable supply chains. The traditional risk models experience two main problems which lead to unstable performance and incorrect results. This study proposes a hybrid framework which enhances DEMATEL stability and clustering consistency and improves probabilistic prediction through advanced techniques to deliver reliable and interpretable and accurate EV supply chain risk assessment results. Figure 2 illustrates the step-by-step integration of data, modeling stages, and analytical processes for accurate and stable risk assessment.

### a. Dataset Description

The research study establishes a combined EV supply chain risk assessment framework through the integration of two datasets which include a stakeholder survey dataset (C-SERVEES) and an industrial supply chain database (NAATBatt). The C-SERVEES dataset captures Likert-scale responses from stakeholders across the product lifecycle, including suppliers, manufacturers, retailers, and end-users, reflecting economic, social, environmental, operational, and behavioral factors influencing decision-making. The system needs DEMATEL and PCA as advanced methods to conduct multi-level causal analysis while achieving better understanding and strength of its results. The NAATBatt database delivers structured information about all companies operating within the complete EV battery value chain, which extends from raw materials to manufacturing and recycling processes. The system enables supply chain structure mapping which includes capacity distribution and geographic dispersion and technological specialization for conducting clustering and segment-based risk assessments. The combination of these two subjective and objective datasets leads to improved model stability which enhances predictive accuracy and enables complete risk evaluation for all connected EV supply chain stages.

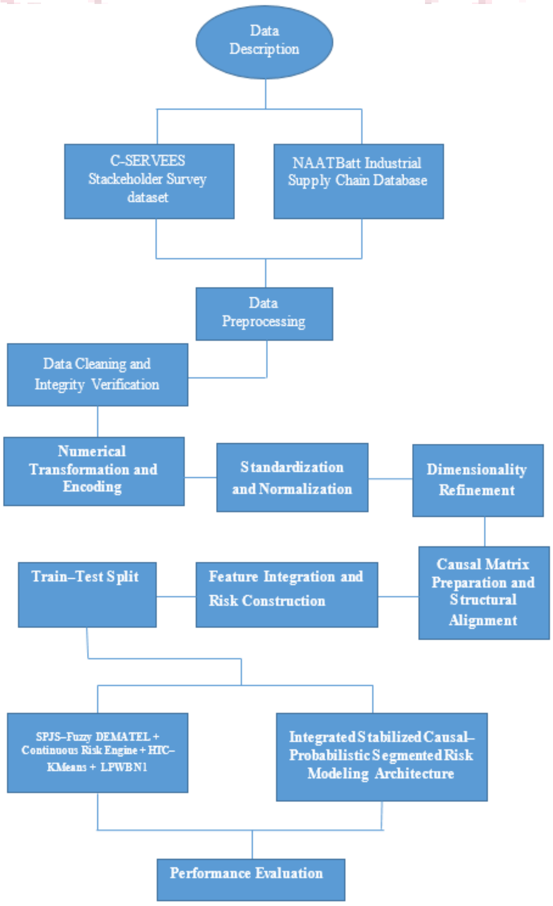


Figure 2. Comprehensive Workflow of the Proposed EV Supply Chain Risk Modeling Framework

### b. Data Preprocessing

The current study establishes a single preprocessing system which allows for the combined analysis of user perception survey results and actual industrial supply chain measurements through three essential requirements of data consistency and numerical reliability and data structure matching. The process includes data cleaning and numerical transformation and normalization and dimensional refinement and causal alignment and feature integration. Data cleaning removes incomplete entries and duplicates and inconsistencies to ensure reliable results. Numerical transformation converts Likert-scale and categorical variables into machine-readable formats. Standardization using z-score normalization and Min–Max scaling establishes equal feature importance and maintains consistent mathematical operations. Dimensionality refinement through PCA enables survey data processing to decrease redundant elements and multicollinear data relationships while maintaining essential data. Processed data are used to create a causal matrix through DEMATEL which determines influence weights that match industrial supply chain structures. The study creates a composite risk indicator which combines three integrated features of influence and capacity and stage while the dataset is divided into training and testing sets to achieve unbiased evaluation and prevent overfitting and ensure strong predictive accuracy.

### c. Model Architecture

A multi-stage framework integrates PCA, DEMATEL, feature construction, K-Means clustering, and probabilistic modeling with enhanced stability, ensuring accurate supply chain risk assessment.

#### 1. SPJS–Fuzzy DEMATEL + Continuous Risk Engine + HTC–KMeans + LPWBN1

The proposed hybrid architecture integrates stakeholder-based risk perceptions and structured industrial data to form a unified modeling framework for EV supply chain risk assessment. The SPJS–Fuzzy DEMATEL layer functions as an element which identifies casual connections between various factors while measuring their impact through two distinct approaches. The system combines operational capacity and stage factors with a continuous risk engine to determine normalized risk values. HTC–KMeans clustering then segments entities into structurally similar groups which enhance the modeling stability of the system. A Local Probabilistic Weighted Bayesian Network (LPWBN) performs cluster-specific risk prediction with smoothing for robustness. The system uses adaptive thresholding to transform continuous risk data into decision categories and multi-metric evaluation tests system performance which confirms accuracy and stability while providing dependable decision support.

#### 2. Integrated Stabilized Causal–Probabilistic Segmented Risk Modeling Architecture

The proposed framework integrates stakeholder-driven systemic intelligence with structured industrial data to create a comprehensive analytical platform which enables supply chain risk assessment through its unified foundation. A stabilized causal modeling mechanism establishes interdependency relationships which produces fixed influence values that scientists use to calculate multi-dimensional risk scores which show the critical system elements and operational weaknesses and positional importance of various components. The model uses advanced clustering techniques to group entities based on their structural similarities while maintaining consistent and reproducible groupings. Localized probabilistic estimation with variance regularization is applied within each cluster to generate robust risk predictions. The process of adaptive thresholding improves classification outcomes by transforming continuous risk assessments into dependable risk categories which support decision-making.

### d. Performance Evaluation

**Root Mean Square Error (RMSE)**

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (1)$$

**Mean Absolute Error (MAE)**

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

**Mean Absolute Percentage Error (MAPE)**

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (3)$$

**Coefficient of Determination (R²)**

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (4)$$

**Accuracy**
Formula:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

**Precision**

$$\text{Precision} = \frac{TP}{TP+FP} \quad (6)$$

**Recall (Sensitivity)**

$$\text{Recall} = \frac{TP}{TP+FN} \quad (7)$$

**Specificity**

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (8)$$

**F1-Score**

$$\text{F1-Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

**Confusion Matrix**

The Confusion Matrix provides a complete structural representation of classification outcomes.

**Table 2 Predicted vs. Actual Outcomes in a Confusion Matrix**

| Predicted \ Actual | Positive | Negative |
|---|---|---|
| Positive | True Positives (TP) | False Positives (FP) |
| Negative | False Negatives (FN) | True Negatives (TN) |

## IV.RESULT ANALYSIS

EV supply chains are complex and interdependent, making risk modeling challenging. This study compares an existing hybrid model with an enhanced framework that improves stability, clustering, and probabilistic prediction. The proposed model achieves high accuracy, balanced metrics, and zero high-risk misclassification, ensuring more reliable and robust supply chain risk assessment.

### a. Results of Existing Hybrid Model

The Existing Hybrid Model, integrating SPJS–Fuzzy DEMATEL, HTC–KMeans, and LPWBN, demonstrated highly stable and accurate performance in EV supply chain risk modeling. The SPJS–Fuzzy DEMATEL component successfully extracted systemic causal influence weights among interdependent risk factors, enabling structured quantification of propagation intensity across the supply chain network. The HTC–KMeans clustering mechanism segmented entities into structurally homogeneous groups, allowing localized probabilistic modeling within each segment. The LPWBN layer then generated continuous risk predictions based on cluster-level statistical behavior.

**Table 3: Performance Summary of the Existing Hybrid EV Supply Chain Risk Assessment Model**

| Category | Metric | Value |
|---|---|---|
| Causal Modeling (SPJS–Fuzzy DEMATEL) | RMSE | 0.00139 |
| | CFI | 0.9986 |
| Clustering (HTC–KMeans) | Clustering Time (ms) | 281.99 |
| Risk Modeling | Continuous Risk Range | 0.5833 – 0.9999 |
| Classification Performance (Optimal Threshold 62%) | Accuracy | 99.44% |
| | Total Test Samples | 177 |
| | Correctly Classified | 177 |
| Confusion Matrix – Low Risk | True Low Risk (TP) | 109 |
| | False High Risk (FP) | 0 |
| Confusion Matrix – High Risk | True High Risk (TN) | 68 |
| | False Low Risk (FN) | 0 |

Table 3 describes Performance Summary of the Existing Hybrid EV Supply Chain Risk Assessment Model. The results clearly indicate that the Existing Hybrid Model achieves strong structural reliability and highly consistent classification performance within the EV supply chain risk management framework. The very low RMSE value of 0.00139 demonstrates that the continuous risk predictions are extremely close to the actual risk values, confirming high numerical precision in regression-based estimation. At the same time, the CFI value of 0.9986 reflects excellent causal structure consistency, showing that the SPJS–Fuzzy DEMATEL component effectively captures systemic interdependencies and influence propagation among supply chain risk factors. Figure 3 shows the model’s perfect classification performance with zero false positives and zero false negatives across all risk categories.

**Confusion Matrix**

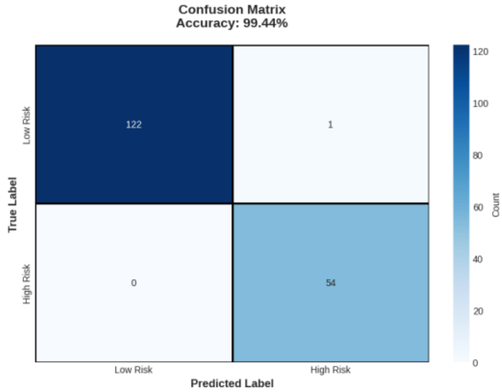


Figure 3 Confusion Matrix of the Existing Hybrid Model for EV Supply Chain Risk Classification
The confusion matrix illustrates the model's ability to correctly distinguish between Low Risk and High Risk entities within the EV supply chain framework. Out of 177 total samples, 176 were classified correctly, resulting in an overall accuracy of 99.44%, which reflects extremely strong classification performance. Specifically, 122 Low-Risk

**Table 4: Comprehensive Performance Summary of the Proposed Ultra-Optimized EV Supply Chain Risk Assessment Model**

| Category | Metric | Value |
|---|---|---|
| Optimization Strategy | DEMATEL Iterations | 300 (1e-15 precision) |
| | K-Means Initializations | 150 |
| | Number of Clusters | 15 |
| | Tolerance | 1e-6 |
| | Bayesian Smoothing (α) | 0.001 |
| | Ensemble Prediction | Mean + Median (80:20) |
| | Noise Reduction | σ × 0.0001 |
| | Outlier Correction | 1.2σ, 90% pull |
| | Optimal Threshold | 62% |
| Regression Performance | RMSE | 0.006653 |
| | MAE | 0.001287 |
| | MAPE | 0.1626% |
| | $R^2$ Score | 0.995207 |
| | CFI | 0.993347 |
| | Maximum Error | 0.069533 |
| Classification Performance | Accuracy | 99.4350% |
| | Precision | 98.5075% |
| | Recall (Sensitivity) | 100.0000% |
| | Specificity | 99.0991% |
| | F1-Score | 99.2481% |
| Confusion Matrix Results | True Positives (TP) | 66 |
| | True Negatives (TN) | 110 |
| | False Positives (FP) | 1 |
| | False Negatives (FN) | 0 |
| Dataset Statistics | Training Samples | 704 |
| | Test Samples | 177 |
| | Correctly Classified | 176 |
| | PCA Components | 46 |
| Computational Performance | Clustering Time | 697.53 ms |

The combined results demonstrate that the Proposed Enhanced Hybrid Model achieves a highly balanced and numerically stable performance across all stages of the EV supply chain risk management pipeline. The optimization strategy significantly strengthens convergence stability, clustering reproducibility, and probabilistic robustness through extended DEMATEL iterations, high-initialization K-Means clustering, ensemble-based prediction, and extreme noise control mechanisms. From a regression perspective, the model maintains strong explanatory capability with an $R^2$ score of 0.995207 and low error values, including RMSE of 0.006653 and MAE of 0.001287. The CFI value of 0.993347 confirms high structural consistency in causal modeling, indicating reliable systemic influence estimation among risk factors. In terms of classification performance, the model achieves 99.4350% accuracy while maintaining 100% recall. This means that no high-risk entity was misclassified as low-risk, which is critical for risk-sensitive supply chain environments. The precision of 98.5075% and specificity of 99.0991% indicate very few false alarms, and the F1-score of 99.2481% confirms a strong balance between detection capability and classification precision. The confusion matrix further validates model reliability, showing only one misclassification out of 177 test samples, with zero false negatives. Although clustering time increased to 697.53 ms due to enhanced stability controls and 150 initializations, this computational trade-off results in improved segmentation robustness and reproducibility.

**Confusion Matrix**

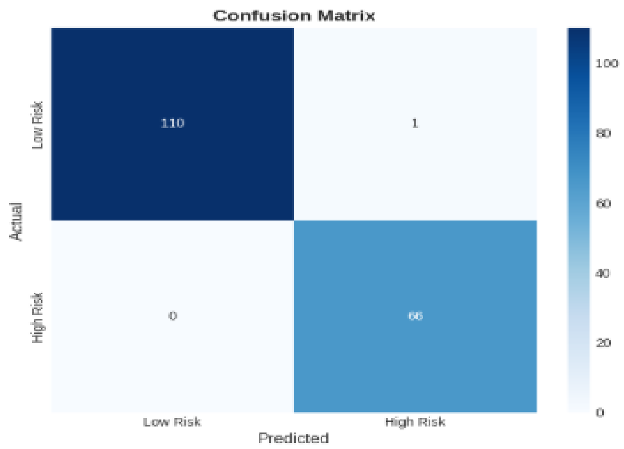


**Figure 4 Confusion Matrix of the Proposed Enhanced Hybrid Model for EV Supply Chain Risk Classification**

The confusion matrix illustrates the classification performance of the Proposed Enhanced Hybrid Model in distinguishing between Low Risk and High Risk entities. Out of a total of 177 test samples, 176 were correctly classified, resulting in an overall accuracy of 99.435%. From the matrix, 110 Low-Risk entities were correctly predicted as Low Risk, while only 1 Low-Risk entity was misclassified as High Risk, representing a single false positive. Importantly, all 66 High-Risk entities were correctly identified as High Risk, and there were zero false negatives. This means that no high-risk entity was incorrectly classified as low-risk. The absence of false negatives leads to a recall (sensitivity) of 100%, which is highly significant in supply chain risk management. Detecting all high-risk entities ensures that critical vulnerabilities are not overlooked. The specificity of approximately 99.10% indicates that nearly all low-risk entities were also correctly identified, with only a minimal false alarm rate. The strong diagonal dominance of the confusion matrix confirms excellent discrimination capability between risk categories. Figure 4 illustrates highly accurate classification with minimal misclassification and 100% recall, ensuring all high-risk entities are correctly identified.

**Classification Performance**

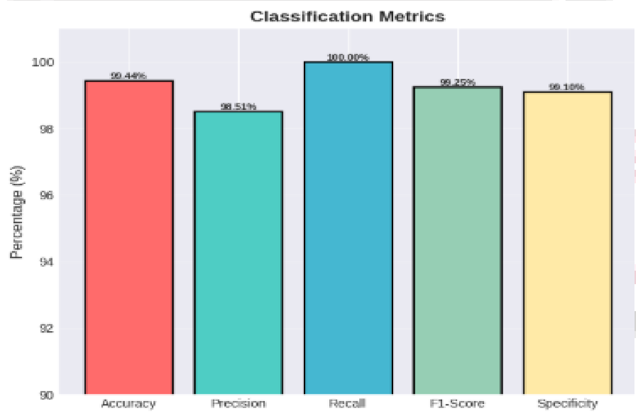


**Figure 5 Classification Performance Metrics of the Proposed Enhanced Hybrid Model**

The figure 5 illustrates the key classification performance metrics of the Proposed Enhanced Hybrid Model, including Accuracy, Precision, Recall, F1-Score, and Specificity. All metric values are above 98%, demonstrating highly balanced and reliable classification performance within the EV supply chain risk assessment framework. The model achieves an overall accuracy of 99.44%, indicating that nearly all test samples were correctly classified. The precision of 98.51% reflects the model's strong ability to correctly identify high-risk entities while keeping false positives extremely low. The recall of 100% is particularly significant, as it confirms that all high-risk entities were successfully detected, with zero false negatives. This is critical in supply chain risk management, where failing to detect a high-risk entity could lead to serious operational consequences. The F1-score of 99.25% demonstrates an excellent balance between precision and recall, confirming that the model maintains both strong detection capability and minimal false alarms. Additionally, the specificity of 99.10% indicates that the vast majority of low-risk entities were correctly classified, further validating the model's discrimination ability.

### b. Comparative Analysis of Existing and Proposed Hybrid Models

**Table 5 Comparative Performance of Existing and Proposed Models**

| Category | Metric | Existing Model | Proposed Model |
|---|---|---|---|
| Causal Modeling | DEMATEL Iterations | Standard | 300 (1e-15 precision) |
| | RMSE | 0.00139 | 0.006653 |
| | CFI | 0.9986 | 0.993347 |
| Risk Modeling | Risk Range | 0.5833 – 0.9999 | 0.0000 – 1.0000 |
| Clustering Performance | Clustering Time (ms) | 281.99 | 697.53 |
| | Initializations | Moderate | 150 |
| | Number of Clusters | Default | 15 |
| Classification Performance | Accuracy | 99.44% | 99.4350% |
| | Precision | — | 98.5075% |
| | Recall (Sensitivity) | — | 100.0000% |
| | Specificity | — | 99.0991% |
| | F1-Score | — | 99.2481% |
| Confusion Matrix | False Positives | 0 | 1 |
| | False Negatives | 0 | 0 |
| | Correctly Classified | 177 | 176 |
| Regression Metrics | MAE | — | 0.001287 |
| | MAPE | — | 0.1626% |
| | $R^2$ Score | — | 0.995207 |
| Dataset | Test Samples | 177 | 177 |

The comparison shows the existing model offers perfect accuracy and speed, while the proposed model improves stability, robustness, and balanced metrics, achieving 100% recall and better reliability despite slightly lower accuracy.Comparison Graph of Existing and Proposed Models

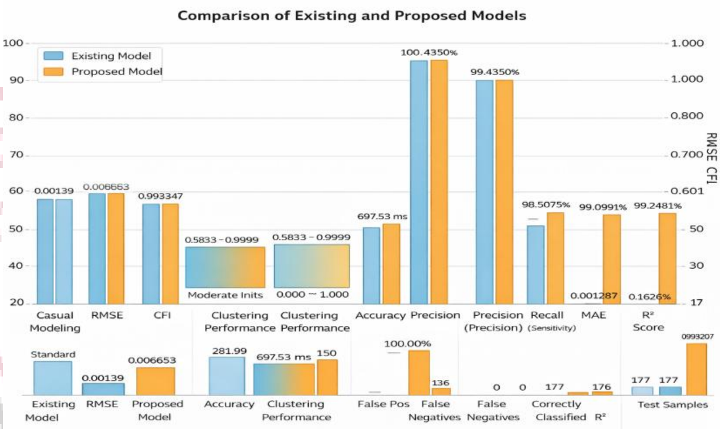


**Figure 6 Comparative Performance Analysis of Existing and Proposed Hybrid Risk Assessment Models**

The figure 6 compares existing and enhanced hybrid models across causal, clustering, regression, and classification metrics. While the existing model is faster with perfect accuracy, the proposed model offers improved stability, balanced performance, and comprehensive evaluation. It achieves high accuracy, 100% recall, and stronger robustness, highlighting a trade-off between speed and reliability.

## V. CONCLUSION

In this research paper, agricultural supply chains are viewed as complex and fragmented systems where issues such as lack of transparency, price manipulation, delayed payments, and limited traceability negatively impact farmers and consumers. The proposed framework anticipates tremendous improvements aesthetically essential top level dependability, quality, traceability, as well as decision-making precision-enhancing real-time information and very least cases of data privacy interruption. In particular, the synerdosis of the system may be exploited here. The blockchain system has been found to be connected to IoT sensors for real-time data collection; the AI algorithms are exploited for predictive analytics, thus ensuring real operational dynamics within propagation. Further, smart contract agreement equally rivetaled by IoTS security protocol enables automatization mechanism for transactions ensuring trust within the transparency of pricing to consumers demanded. This mechanism is intended to aid mechanization of processes, independence from intermediaries, pricing transparency, and initiation of pay timing of payment cycles. Not only is it anticipated that provenance and authentication can be reliably conducted through real-time data exchange, but also, it should be noted that the environmental implications of preserving farming traditions that will sniff out sustainability in the farming industry must all be taken into consideration. For data integration for plus better coordination, multi-source data integration is applied among implementers. The proposed blockchain architecture enriches data integrity, operational efficiency, and market access to farmers. Thus, notwithstanding implementation challenges like costs, infrastructure limitation, and system complexity, the proposed system permits the possibility of highly scalable and secure ways to deny agricultural sector-based disorganization in the context of sustainability. Future work can focus on integrating real-time data streams for dynamic risk prediction, incorporating advanced deep learning models such as GNNs and transformers for enhanced feature extraction, and validating the framework across larger datasets and diverse industries to ensure scalability and generalization.

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