# Using Machine Learning to Enhance Market Forecasting and Financial Sustainability of Agribusiness Enterprises

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*Abstract*— Agribusiness enterprises operate in highly volatile markets characterized by commodity price fluctuations, perishability risks, seasonal production cycles, and limited access to credit, all of which threaten financial sustainability. Machine learning (ML) offers advanced capabilities for extracting predictive insights from large and complex datasets, thereby improving market forecasting, financial risk assessment, and enterprise decision-making. This paper reviews the application of machine learning in enhancing market forecasting and financial sustainability within agribusiness enterprises. The review covers commodity price prediction, demand and supply chain forecasting, credit risk assessment, financial distress prediction, firm performance evaluation, and sentiment analytics. A systematic narrative review was conducted using peer-reviewed literature sourced from Scopus, Web of Science, PubMed, Nature, Frontiers, Springer, ScienceDirect, Emerald, and the Consensus academic search repository. Thirty high-quality studies spanning agricultural economics, financial analytics, supply chain management, and machine learning were synthesized. The findings indicate that hybrid deep learning models outperform traditional forecasting approaches in predicting agricultural commodity prices. Long Short-Term Memory (LSTM) models consistently surpass ARIMA models in forecasting accuracy. Ensemble machine learning techniques, including Rotation Forest and Logit Boosting, effectively assess credit risk among agricultural SMEs, with financial leverage, current ratio, profit margin, and sales growth identified as key predictors. Machine learning-based demand forecasting improves supply chain efficiency and inventory management, while sentiment analysis using natural language processing enhances market intelligence by incorporating signals from news and social media sources. Overall, machine learning is transforming agribusiness management by strengthening market forecasting, financial risk management, and supply chain optimisation. However, challenges related to data governance, model interpretability, and equitable access remain critical areas for future attention.

**Keywords:** Machine learning; market forecasting; agribusiness; financial sustainability; commodity price prediction; credit risk; supply chain optimisation; sentiment analysis.

## I. INTRODUCTION

Agriculture is foundational to global economic stability, contributing approximately 4% of global GDP and reaching a share of 25% in developing countries [1]. Agribusiness enterprises, spanning input supply, primary production, processing, and distribution, operate at the intersection of biological, environmental, and financial risk in ways that few other sectors must contend with simultaneously. Commodity prices for staple crops fluctuate in response to climate events, geopolitical disruptions, exchange rate movements, and speculative market activity, creating planning and investment environments of exceptional complexity [2]. At the enterprise level, these external volatilities manifest as revenue uncertainty, inventory risk, credit rationing, and strategic planning difficulties that threaten financial sustainability across the value chain.

Traditional statistical and econometric approaches to agricultural market forecasting, including Autoregressive Integrated Moving Average models and Vector Autoregression frameworks, were developed in data-constrained environments and rely on assumptions of linearity and stationarity that agricultural time series frequently violate [3]. As high-frequency price data, remote sensing outputs, supply chain transaction records, social media feeds, and macroeconomic indicators are increasingly available in digital form, the analytical limitations of classical approaches have become a binding constraint on agribusiness decision quality.

Machine learning, encompassing classical ensemble methods, recurrent neural networks, deep learning architectures, and natural language processing, resolves many of these limitations by learning directly from complex, non-linear data without requiring pre-specified functional forms. A comprehensive topic modelling analysis of 1,114 Scopus publications on machine learning in agriculture identified advanced financial and technological applications as one of six primary research themes, demonstrating the growing recognition of machine learning as an enterprise financial management tool rather than merely a production optimisation technology [4].

Despite this recognised importance, the literature on machine learning for agribusiness financial sustainability remains dispersed across commodity markets research, supply chain analytics, financial distress prediction, and credit risk modelling. No unified review synthesises these streams through the lens of enterprise financial sustainability. This paper fills that gap. The paper is structured as follows: Section

2 describes the methodology; Section 3 analyses machine learning approaches to commodity price forecasting; Section 4 examines demand forecasting and supply chain financial optimisation; Section 5 addresses financial distress prediction and credit risk assessment for agribusiness firms; Section 6 investigates machine learning for firm performance prediction; Section 7 evaluates sentiment analysis as a market intelligence tool; Section 8 presents a synthesis framework and policy recommendations; and Section 9 concludes.

## II. METHODOLOGY

### A. *Search Strategy and Database Selection*

A systematic narrative review methodology was employed to synthesise evidence spanning agricultural economics, financial analytics, supply chain management, and machine learning science. Academic databases searched included Scopus, Web of Science, PubMed, Nature Publishing Group, Frontiers journals, Springer Nature, ScienceDirect, Emerald Publishing, and the Consensus AI academic search engine. Boolean search clusters were designed across five thematic domains: (a) machine learning AND commodity price forecasting AND agribusiness; (b) deep learning AND agricultural market prediction AND financial sustainability; (c) machine learning AND credit risk AND agricultural SME; (d) machine learning AND financial distress AND firm performance AND agriculture; and (e) sentiment analysis AND NLP AND commodity price AND agribusiness. Searches were conducted in May to June 2026 without publication date restriction.

### B. *Eligibility Criteria and Synthesis*

Inclusion criteria required studies to: (i) be published in peer-reviewed journals, peer-reviewed book chapters, or peer-reviewed conference proceedings indexed in recognised academic databases; (ii) report empirical, systematic review, or analytical framework findings relevant to machine learning applications in agribusiness market forecasting or financial sustainability; and (iii) be written in English. Thirty references were retained after quality and relevance screening. A narrative synthesis approach was applied, organising evidence thematically across the five domains described above.

## III. MACHINE LEARNING FOR COMMODITY PRICE FORECASTING

### A. *The Challenge of Agricultural Price Volatility*

Agricultural commodity markets exhibit characteristics that are fundamentally hostile to classical forecasting methods. Price series for major staple crops including wheat, maize, and rice are characterised by non-stationarity, non-normality, and non-linearity in both supply and price data [2]. External volatility sources including climate events, market speculation, and policy interventions further compound these difficulties by introducing structural breaks that invalidate assumptions embedded in ARIMA and related linear models. A systematic review of machine learning methods for staple crop price prediction, drawing on the Scopus database and covering studies published up to December 2024, found that hybrid deep learning models consistently outperform traditional methods and represent the current methodological state of the art [2].

The scope of the forecasting challenge across agribusiness is substantial. Agriculture accounts for 4% of global GDP, and forecasting errors in commodity markets cascade through enterprise revenue projections, procurement costs, inventory valuations, and credit servicing capacity [1]. For enterprises in developing economies, where agricultural commodity dependence is highest and hedging instruments are least accessible, accurate price forecasting is not merely a competitive advantage but a determinant of organisational survival.

### B. *Performance of Machine Learning Algorithms in Price Prediction*

A comprehensive empirical study evaluating traditional stochastic models, machine learning techniques, and deep learning approaches for forecasting prices of 23 agricultural commodities using daily wholesale price data from January 2010 to June 2024 found that advanced deep learning architectures including LSTM, Gated Recurrent Units, and Echo State Networks generally outperformed classical benchmarks, with LSTM demonstrating particular strength in capturing long-term dependencies in sequential price data [5]. The study confirmed that integrating real-time data including weather patterns and global market trends into forecasting systems enables more accurate multi-sector response coordination and supports sustainable agricultural growth [5].

Hybrid architectures achieve the most robust results in operational deployments. An ARIMA-LSTM hybrid demonstrated superior performance over either component model alone on volatile agricultural price series, reducing prediction error on non-stationary data that pure statistical approaches handle poorly [6]. A quadratic decomposition technology combined with LSTM for agricultural commodity futures prediction showed strong empirical results on wheat, maize, and sugar futures in Chinese markets, with the decomposition pre-processing step resolving residual noise problems that impair standalone LSTM performance [7]. A novel hybrid SARIMA-LSTM model designated HySALS was developed specifically for global staple commodity price

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forecasting across wheat, millet, sorghum, and maize data, demonstrating superior forecast accuracy across multiple developing country markets [8].

### C. *Text Mining and Hybrid Forecasting Frameworks*

A methodological landscape analysis employing Latent Dirichlet Allocation text mining across agribusiness forecasting publications from 2015 to 2022 found that ML-hybrid approaches accounted for 41.95% of all forecast method usage, confirming their dominance in current practice, with pure statistical approaches at 29.31%, neural network approaches at 14.94%, and ensemble methods at 4.60% [3]. This distribution reflects the practical finding that no single algorithm type commands consistent superiority across commodity types and market regimes: hybrid frameworks combining statistical foundations with machine learning flexibility deliver the most reliable enterprise-grade forecasting performance.

A comprehensive commodity price forecasting framework integrating text mining from social media with machine learning demonstrated that dynamic topic sentiment features constructed from online texts, combined with statistical variables and feature selection, outperform purely quantitative forecasting models for pork and soybean futures prices [9]. This confirms the value of unstructured data as a complementary input to structured price and volume time series in enterprise market intelligence systems.

| Algorithm Class | Key Performance Finding | Agribusiness Application Domain | Evidence Source |
|---|---|---|---|
| LSTM (standalone) | Highest R2 and lowest MAE vs ARIMA | Commodity price and futures forecasting | [5, 6] |
| ARIMA-LSTM Hybrid | Reduces error on volatile price series | Agricultural commodity market planning | [6] |
| HySALS (SARIMA-LSTM) | Superior accuracy across five global commodities | Global staple crop price forecasting | [8] |
| Rotation Forest and Logit Boosting | Accurate SME credit risk differentiation | Agricultural SME credit assessment in Africa | [13] |
| Random Forest and XGBoost | Consistently high commodity price accuracy | Commodity price and firm performance | [2, 16] |
| RNN (supply chain) | 15% MSE reduction over traditional methods | Supply chain demand forecasting | [12] |
| GPR (Gaussian Process) | RRMSE 0.2040%, CC 0.99929 | Wholesale price index forecasting | [10] |

*Table 1: Performance Benchmarks of Key Machine Learning Algorithms in Agribusiness Market Forecasting and Financial Applications*

## IV. DEMAND FORECASTING, SUPPLY CHAIN OPTIMISATION, AND ENTERPRISE PROFITABILITY

### A. *Machine Learning in Agri-Food Supply Chain Management*

Supply chain management is among the most financially consequential operational domains for agribusiness enterprises, given the perishability of products, the seasonality of supply, and the time-sensitivity of distribution. A comprehensive review of machine learning demand forecasting and supply chain performance, analysing 2,561 publications from Scopus spanning 2020 to 2025, documented that machine learning drives value creation across demand forecasting, real-time logistics decision making, and inventory management simultaneously [10]. The compound annual growth rate in machine learning and agriculture supply chain publications reached 16.37% from 2000 to 2024, with publications in 2023 and 2024 reaching 206 and 273 respectively, reflecting rapidly accelerating practitioner and academic interest [4].

A study on enhancing supply chain forecasting with machine learning found that Recurrent Neural Networks reduce mean squared error by 15% over traditional approaches in demand prediction tasks, while reinforcement learning agents minimise inventory turnover and lead times to enhance supply chain efficiencies [11]. These findings directly translate to enterprise financial sustainability: reduced forecast error lowers excess inventory carrying costs, reduces stockout losses, and improves working capital utilisation. A comprehensive review of dairy supply chain machine learning applications documented that advanced algorithms including LSTM networks, federated learning approaches, and real-time IoT integration collectively improve operational efficiency, reduce product wastage, and enable actionable decision making that translates to measurable financial gains for dairy enterprises [12].

### B. *Harvest Timing and Market Entry Optimisation*

A distinctive machine learning application with direct profitability implications for agribusiness enterprises is the optimisation of harvest timing and market entry decisions. A study developing a predictive model for profitable crop

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harvesting based on market dynamics trained machine learning models on historical price data including minimum price, maximum price, quantity, average price, and date, demonstrating that ML can determine the optimal harvest window for profit maximisation in ways that conventional experience-based approaches systematically fail to capture [13]. The study confirmed that farmers and agribusiness operators who relied on intuition and historical norms consistently leave margin on the table relative to model-informed timing strategies.

This application is particularly consequential for agribusiness enterprises in markets characterised by intra-seasonal price dispersion, where harvesting and selling even days earlier or later can shift enterprise margins substantially. The transformative AI-driven forecasting review further documented case evidence of North American food processing facilities where real-time model adaptation ensured accuracy and operational relevance, with the caveat that continuous data input requirements represent an access barrier for smaller operations [14].

## V. FINANCIAL DISTRESS PREDICTION AND CREDIT RISK ASSESSMENT

### A. *Machine Learning for Agricultural SME Credit Risk*

Access to finance is a structural constraint on agribusiness enterprise growth, particularly for small and medium-sized enterprises that face inherently higher credit risk, stricter collateral requirements, and less favourable credit pricing than larger counterparts [15]. Machine learning offers financial service providers superior tools for differentiating between low and high credit risk agricultural enterprises, enabling more accurate and inclusive credit allocation that supports agribusiness financial sustainability.

A landmark study proposing a novel hybrid ensemble machine learning approach for forecasting credit risk of agricultural SME investments in Agriculture 4.0 through supply chain finance employed Rotation Forest and Logit Boosting algorithms trained on data from 216 agricultural SMEs, 195 leading enterprises, and 104 financial service providers operating in the African agricultural sector [15]. Beyond classical financial ratios, the study found that current ratio, financial leverage, profit margin on sales, and growth rate of sales are the key variables influencing credit risk, with supply chain finance relationships providing additional predictive power not captured by firm-level balance sheet data alone [15]. These findings directly inform agribusiness enterprise financial strategy: firms that demonstrate strong supply chain integration, positive sales growth trajectories, and controlled financial leverage access credit more readily and at lower cost.

### B. *Machine Learning for Broader Financial Distress Prediction*

Financial distress prediction, encompassing early warning of bankruptcy, liquidity crisis, and operational failure, is a domain where machine learning has demonstrated consistent superiority over classical discriminant analysis and logistic regression approaches. A systematic review of machine learning methods for financial distress prediction, examining the literature through 2025, confirmed that machine learning models have emerged as essential tools for financial difficulty prediction, leveraging expanding databases and processing capacity to generate predictions that surpass both statistical and human expert benchmarks [16].

A study applying Random Forest, Artificial Neural Networks, and logistic regression to a dataset of 1,111 companies processed through India's National Company Law Tribunal resolution and liquidation procedures documented that ML approaches substantially improve the compatibility of distress prediction with the decision-making needs of investors, auditors, creditors, and regulators [17]. Research advancing credit rating prediction through machine learning demonstrated that sector-specific models yield better predictive accuracy by accounting for structural differences across industries, a finding with direct implications for agribusiness-specialised financial institutions seeking to refine their enterprise assessment capabilities [18]. Machine learning for farmer credit risk assessment in the Industry 4.0 era demonstrated that model frameworks integrating non-traditional data, including digital transaction records and supply chain payment histories, reduce credit risk misjudgement caused by weak correlations in conventional evaluation systems [19].

## VI. MACHINE LEARNING FOR AGRIBUSINESS FIRM PERFORMANCE PREDICTION

### A. *Beyond Financial Ratios: Integrated Firm Performance Models*

Financial sustainability at the enterprise level extends beyond avoiding distress; it encompasses the capacity to generate returns, grow revenue, attract investment, and create durable competitive advantage. Machine learning is increasingly applied to predict firm performance across these broader dimensions, drawing on data inputs that range from financial statements and market position indicators to operational metrics and competitive intelligence.

A systematic review of machine learning in predicting firm performance, examining 70 studies published between 2013 and 2023, found that the field has moved beyond traditional financial metrics to incorporate a broad range of attributes encompassing financial health, market positioning, operational efficiency, and innovation indicators [20]. This expansion of the input feature space captures dimensions of agribusiness enterprise performance that balance sheet analysis misses entirely, including supply chain quality, customer relationship depth, and management capability proxies accessible through digital data streams. The review confirmed that no single algorithm consistently dominates firm performance prediction; rather, ensemble methods and hybrid architectures deliver the most robust performance across varying data environments and firm types [20].

### B. *Optimising Harvest and Market Strategy for Profitability*

A Frontiers in Computer Science study developing a predictive model for profitable crop harvesting based on market dynamics integrated machine learning with real-time market price data to recommend optimal harvest windows, demonstrating that agribusiness operators equipped with such models can extract materially higher margins than those relying on experience and intuition [13]. The alignment between production planning, harvest timing, and market price trajectories requires the kind of multi-variable optimisation that machine learning performs well and that human planners consistently underperform on due to cognitive and information processing limitations.

The structured review of artificial intelligence in agribusiness confirmed that machine learning enhances agribusiness profitability, sustainability, and strategic resilience by enabling resource management and supply chain optimisation that allow for real-time monitoring and informed decision-making [21]. Enterprise-level machine learning implementations in agrifood processing further documented that models integrating IoT sensor data, historical sales records, and external price indices deliver prediction accuracy sufficient to support operational decisions about procurement timing, production scheduling, and pricing strategy that directly shape enterprise financial performance.

## VII. SENTIMENT ANALYSIS AND MARKET INTELLIGENCE FOR AGRIBUSINESS

### A. *NLP and Machine Learning for Agricultural Price Intelligence*

Natural language processing and sentiment analysis represent an increasingly important dimension of machine learning powered market forecasting for agribusiness enterprises. Agricultural commodity prices are influenced not only by supply and demand fundamentals but by information flows, expectations, and sentiment expressed in news media, social media platforms, and policy announcements. Extracting quantitative signals from these unstructured text data sources and integrating them with structural price forecasting models enriches enterprise market intelligence in ways that improve both forecast accuracy and the speed of price signal detection.

Research investigating whether sentiment analysis brings more responsive and comprehensive commodity price forecasting confirmed that NLP and machine learning techniques used to assess sentiment expressed in social media posts, news articles, and online discussions relating to commodities provide leading indicator signals of potential price changes before they are reflected in traded prices [22]. Social media sentiment acts as a leading indicator, providing early warning of shifts in market sentiment that subsequently influence commodity price trajectories, enabling agribusiness enterprises to adjust procurement, inventory, and hedging strategies ahead of market movements [22].

### B. *Comprehensive Text Mining Frameworks for Commodity Forecasting*

A comprehensive commodity price forecasting framework developed in the Journal of Forecasting used text mining methods to construct dynamic topic sentiment features from online platform texts, combining these with modal price series features extracted via the Integrated-EEMD-VMD-SE method and statistical variables to form a multi-source input to comparative random forest, LSTM, and multilayer perceptron models [9]. The framework demonstrated that integrating text-derived sentiment with numerical price data consistently outperforms purely quantitative models for pork and soybean price forecasting, two strategically important commodities for agribusiness enterprises across Asia and beyond [9].

A novel Bayesian-tuned Gaussian Process Regression model for composite wholesale agricultural price index forecasting achieved a correlation coefficient of 0.99929 and a relative root mean square error of 0.2040% in out-of-sample validation across data from September 2005 to April 2025, representing a level of predictive accuracy that directly supports enterprise-level financial planning, hedging strategy formulation, and procurement cost management [10]. This class of model, when updated with near-real-time price and text data, provides agribusiness enterprises with a continuously refreshed market intelligence capability that replaces periodic analyst reporting with dynamic, data-driven insight.

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| Functional Domain | ML Contribution to Financial Sustainability | Priority Implementation Constraint |
|---|---|---|
| Commodity price forecasting | Hybrid LSTM models outperform ARIMA across staple crops | Region-specific and low-data market adaptation |
| Demand and supply chain forecasting | 15% MSE reduction; inventory and wastage optimisation | Continuous data pipeline and IoT integration costs |
| Harvest and market entry timing | Model-informed timing consistently improves farm margins | Last-mile price data access for smallholder operators |
| Credit risk and distress prediction | Ensemble methods improve SME credit access and reduce misjudgement | Non-financial data availability and privacy governance |
| Firm performance prediction | Multi-attribute models capture operational and strategic value | Sector-specific model calibration requirements |
| Sentiment and market intelligence | NLP sentiment provides leading price signal from unstructured data | Multilingual processing and platform data access |

*Table 2: Machine Learning Contributions to Agribusiness Financial Sustainability Across Functional Domains and Priority Implementation Constraints*

## VIII. INTEGRATED FRAMEWORK AND POLICY DIRECTIONS

### A. *Unified Machine Learning Framework for Agribusiness Financial Sustainability*

The evidence reviewed across Sections 3 to 7 supports a unified four-layer machine learning framework for agribusiness enterprise financial sustainability. The first layer is market intelligence, encompassing commodity price forecasting models, sentiment analytics, and macroeconomic signal processing that inform revenue expectations and procurement cost management. The second layer is operational decision support, covering demand forecasting, supply chain optimisation, harvest timing, and inventory management that translate market intelligence into operational actions. The third layer is financial risk management, incorporating credit risk assessment, financial distress early warning, and enterprise performance monitoring that protect the financial integrity of the firm. The fourth layer is strategic positioning, using firm performance prediction and scenario modelling to guide investment, growth, and market diversification decisions that build long-term financial sustainability.

These layers are not independent; they form an integrated analytical ecosystem in which market intelligence informs operational decisions, operational outcomes feed into financial risk assessments, and both inform strategic positioning. Machine learning architectures that operate across all four layers, drawing on shared data infrastructure and updating models continuously as new data arrives, deliver value that exceeds the sum of domain-specific deployments. Hybrid models combining LSTM temporal modelling with Random Forest or Gradient Boosting ensemble interpretability deliver the best balance of predictive accuracy, adaptability, and enterprise-grade explainability [2, 5, 15].

### B. *Policy Recommendations*

Realising machine learning value for agribusiness financial sustainability requires deliberate policy action across four priority areas. First, commodity market data infrastructure must be strengthened in developing economies, where agribusiness dependence is greatest and price data availability is most constrained. Public investment in standardised, open-access agricultural price databases, supply chain transaction registries, and weather and soil data networks creates the shared data commons on which enterprise machine learning systems depend [3, 8].

Second, machine learning model explainability standards should be established for financial applications in agribusiness, requiring that credit risk, financial distress, and price forecasting models used by financial institutions and enterprises generate interpretable outputs accessible to non-technical decision makers. Regulatory adoption of explainability frameworks modelled on SHAP and LIME standards as conditions for financial product approval would accelerate trust and adoption [16, 18]. Third, digital skills development for agribusiness managers must encompass data literacy and basic machine learning interpretation capabilities, enabling enterprise leaders to engage productively with model outputs rather than treating them as opaque recommendations. Fourth, international development finance should specifically support the adaptation of machine learning market forecasting tools to smallholder and cooperative agribusiness contexts in developing economies, where the gap between ML capability and enterprise financial sustainability need is most acute [21].

## IX. CONCLUSION

This paper has presented a comprehensive review of machine learning applications that enhance market forecasting and financial sustainability of agribusiness enterprises. The evidence reviewed across commodity price prediction, demand and supply chain forecasting, financial distress and credit risk assessment, firm performance prediction, and sentiment analytics establishes machine learning as a transformative technology for agribusiness financial management.

The convergence of findings across these domains is compelling. Hybrid deep learning models, particularly LSTM-based architectures combined with statistical preprocessing, consistently outperform classical approaches on agricultural commodity price series. Ensemble machine learning frameworks accurately differentiate low and high credit risk

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among agricultural SMEs, including in data-constrained African contexts. Supply chain demand forecasting with machine learning reduces forecast error by 15% over traditional approaches, translating directly to inventory cost savings and working capital improvements. Sentiment analysis using NLP provides leading indicator signals that enrich market intelligence with information from unstructured text sources that classical models cannot access.

The cumulative financial sustainability impact of deploying machine learning across all four layers of the proposed framework is substantially larger than any single application domain delivers in isolation. Agribusiness enterprises that invest in integrated machine learning analytics capabilities position themselves to navigate commodity price volatility, manage credit risk, optimise operational decisions, and sustain competitive advantage in ways that firms relying on traditional analytical approaches cannot match.

The principal challenge is not technical capability but equitable access. Smallholder farmers, cooperative enterprises, and small agribusinesses in developing economies face the steepest machine learning access barriers while confronting the most severe financial sustainability risks. Closing this gap requires the coordinated policy action, data infrastructure investment, and capacity building described in Section 8. Where these enabling conditions are created, machine learning will function not merely as a tool for sophisticated commercial agribusiness operators but as a broadly accessible resource for financial sustainability across the full agribusiness enterprise spectrum.

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