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Data-Driven Decision-Making for Financial Sustainability in the Flower Market Using Predictive Analytics

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Predictive Analytics, Financial Sustainability, Flower Market, Demand Forecasting, Dynamic Vortex Search-driven Intelligent Long Short-Term Memory (DVS-ILSTM), Resource Optimization

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ABSTRACT

The flower market is highly sensitive to seasonal trends, supply chain disruptions, and demand volatility, making accurate forecasting essential for financial sustainability. Despite the availability of data, many businesses in the sector struggle to make informed decisions due to unpredictable market behavior. This research introduces a predictive analytics-based framework named Dynamic Vortex Search-driven Intelligent Long Short-Term Memory (DVS-ILSTM) to support data-driven decision-making. It gathers historical sales data, market trends, and environmental indicators from publicly available sources and internal company records. For pre-processing, the Min-Max Scaling technique is used to normalize the data, ensuring all variables are on the same scale for better model performance. Feature extraction is achieved through Independent Component Analysis (ICA), allowing critical patterns to emerge. The DVS-ILSTM combines Vortex Search optimization to tune hyper parameters dynamically and the ILSTM model to capture temporal dependencies for accurate demand forecasting. This hybrid model supports decisions on production, inventory, and distribution with higher precision. By integrating predictive analytics into operational planning, businesses manage resources, reduce waste, and enhance profitability. Experimental results show improved forecasting performance across RMSE and MAE metrics compared to conventional models, as well as a higher R^2 value (67%). The proposed approach strengthens strategic planning and contributes directly to the financial sustainability of businesses operating in the competitive flower market

1. INTRODUCTION

The flower market, a vibrant segment within the global horticulture industry, plays an essential role in economies worldwide, contributing to both commercial and social sectors. Whether through the sale of fresh-cut flowers, potted plants, or ornamental plants, the industry supports millions of jobs, spanning from growers and wholesalers to florists, event planners, and retailers (Darras, 2024). Financial sustainability is the ability of companies in the industry to run their operations profitably and effectively to maintain both long-term stability and short-term viability (Misbauddin et al., 2023) (Barry, 2025). The flower sector is highly seasonal; for certain flowers, demand peaks on specific holidays, events, or seasons, for example chrysanthemums take over the marketplace through the autumn months in many cultures (Eiglsperger et al., 2024). However, demand for flowers is influenced by a variety of unpredictable factors, including weather conditions, local events, and shifting consumer preferences (Haselbeck et al., 2022). To achieve financial sustainability, strategies are adopted to maximize income and minimize costs and also consider efficient allocation of resources while making the system less vulnerable to external shocks, such as market fluctuations and uncertainties arising from climate. Financial decision making for the flower market faces challenges such as data quality issues, model interpretability, high implementation costs, over reliance on historical data and potentially leading to suboptimal financial strategies. The aim is to improve the decision making in the flower market by using predictive models for better planning and resource management, which ultimately assists business to increase profits and reduce losses. This research introduces a predictive analytics-based framework named Dynamic Vortex Search-driven Intelligent Long Short-Term Memory (DVS-ILSTM) to support data-driven decision-making

2. RELATED WORK

Using a collection of Red Green Blue (RGB) values from drone-captured images as the input, the research provided a Machine Learning (ML) approach to categorize the crop varieties as the expected result. Underdeveloped or damaged flower field regions were identified using Holistically Edge Detection (HED) (Pramanick et al., 2025). The techniques addressed the issue of irregular cultivation area surveillance with notable accuracy and efficiency. The model suffers from overfitting to the training data, leading to reduced performance when applied to unseen data with different crop varieties. Deep learning (DL) based techniques have improved the timing of chemical thinning by calculating the distribution of flower blossom phenology from RGB images (Wang et al., 2021). The reliance on 2D imaging limited the ability to capture depth information, and analyzed flower clusters in certain contexts. Artificial Intelligence (AI) defined the distribution procedure point, transport supplies, and other distribution criteria through contract compilation (Majdalawieh et al., 2021). Smart contract for the flower supply chain in the research outlined the procedure, increased efficiency, as well as reduced industry costs and flower waste. It compared the proposed smart contract to traditional transaction techniques. It limits the scalability and adoption of the system. The application of AI in floriculture was studied, and the results monitor plant conditions, temperature, weather, and soil nutrients, boosting floral yield while reducing waste. The flower manufacturing and transportation industries enhanced efficiency and decreased waste by implementing AI (Farjana et al., 2024). It discouraged future paths in the use of AI in floriculture. AI approaches struggle with the unpredictability of natural variables affecting flower growth and quality. Deep Learning (DL) was used in research to identify chrysanthemum phenotypes (Nguyen et al., 2024). The algorithm identified essential aspects from flower data to two-dimensional representations for classifying the flower patterns. The experimental findings revealed that recognition accuracy ranging was high. The approach lacks in handling variations caused by environmental factors like lighting conditions.

3. METHODOLOGY

The purpose of this research is to use a predictive model to enhance decision-making in the flower market through improved planning and resource management, which eventually helps businesses to boost revenues and cut losses. Dataset is gathered from kaggle website, after that, data preprocessing is conducted using min max normalization, feature extraction using ICA, and predictive analytics-based framework DVS-ILSTM model to capture temporal dependencies for accurate demand forecasting.

3.1 Dataset

The data is gathered from the kaggle website: https://www.kaggle.com/datasets/zoya77/flower-market-financial-trend-forecasting-data. This dataset replicates flower market sales activities, with the purpose of supporting predictive analytics for financial sustainability. It comprises 3,426 daily data with a variety of factors influencing demand and supply. Weather, promotions, inventory, competitive pricing, and event indications are all factors to consider. The dataset combines internal firm indicators and external market circumstances. It is designed to represent real-world seasonal and dynamic trends in the flower business. This data enables experimentation to enhance company decision-making and operational efficiencies.

3.2 Pre-processing

After gathering the dataset, pre-processing involves addressing missing values, removing duplication, correcting errors and assists to clean up the data. Flower market financial trend forecasting data is normalized using Min-Max scaling ensuring all variables are on the same scale for better model performance. This technique ensures that flower market financial trend forecasting data are comparable and provides normalized values using equation (1).

$$Y_m^j \frac{y - y_{min}}{y_{max} - y_{min}} \quad (1)$$

Where y_{min} and y_{max} are minimum and maximum value of y separately, y is the set of detected values.

3.3 Feature extraction using Independent Component Analysis (ICA)

After preprocessing the flower market financial trend forecasting data, feature extraction is carried out using ICA method to identify and isolate statistically independent components from the sales data, market trends, and environmental indicators. By extracting meaningful features, ICA improves the model's capability to capture underlying patterns, improving the accuracy of demand forecasting and supporting data-driven decision-making. The linear model ICA has been extensively utilized to conduct feature extraction and data redundancy reduction for linear models. However, most data distributions are intricately and adequately modeled by a linear model. The basic idea of the recommended ICA is to employ the kernel method to translate the input data to an assumed feature spaceΨ. First, the feature space F is whitened to reflect the input data X. Where, $(\Lambda^{\Psi})^{-1}$ is the covariance matrix of eigenvalues and eigenvectors matrix is denoted as $(W_P^{\Psi})^T\Psi(x)$. The whitened data is expressed as X_w^{Ψ} in Equation (2). The inner product of the features is represented by (3).

$$X_w^{\Psi} = (W_P^{\Psi})^T\Psi(x) = (\Lambda^{\Psi})^{-1}\alpha^T k \quad (2)$$

$$U_I^{\Psi} = W_I^{\Psi} X_I^{\Psi} \tag{3}$$

Where I is the identity matrix and (U_I^{Ψ}) denotes the current state of the features representation using Equation (4), and Equation (5) represents $k(x, y)$ kernel function and d is the degree polynomial.

$$\Delta W_I^{\Psi} = \left[I + \left(I - \frac{2}{1+e^{-U_I^{\Psi}}}\right)(U_I^{\Psi})\right] W_I^{\Psi} \tag{4}$$

$$S = W_I^{\Psi}(\Lambda^{\Psi})^{-1}\alpha^T k(x, y) \tag{5}$$

$$k(x, y) = (x.y)^d \tag{6}$$

Kernel of a Gaussian is represented by$k(x, y)$ and sigmoid kernel is represented by $k(x, y)d$. As indicated in equation (6), it presented a cosine kernel function derived from the polynomial kernel function. It provides feature extraction performance that is superior to the polynomial kernel function:

$$\tilde{k}(x, y) = \frac{k(x,y)}{\sqrt{k(x,x)k(y,y)}} \tag{7}$$

Where k is the kernel of a polynomial equation (7), every fresh kernel function is derived from the kernel$\tilde{k}(x, y) = c(x)c(y)k(k, y)$. The legitimate kernel function (x) is a positive real-valued function y cosine kernel function.

3.4 Dynamic Vortex Search-driven Intelligent Long Short-Term Memory (DVS-ILSTM)

This research introduces a predictive analytics-based framework, DVS-ILSTM, to support data-driven decision-making. LSTM approach designed to capture temporal dependencies in sequential data. The flower market is characterized by complicated, time-dependent patterns in demand, price, and other financial variables. DVS is intended to balance global and local search. The global search enables it to investigate a wide variety of potential solutions, whereas the local search concentrates on refining the solution after promising regions have been identified.

3.4.1 Intelligent Long Short Term Memory (ILSTM)

The ILSTM approach is utilized for financial trend prediction to enhance sustainability in the floral industry by employing intelligent optimization techniques to efficiently forecast market demand. It builds a successful predictive model for data-driven decisions on increasing long-term financial viability and growth in the flower market industry while performing feature selection on historical data of finance and market trends. The cellular state model resembles an industrial belt. The conveyor belt has the greatest number of linear connections. ILSTM provides an internal mechanism known as a "gate" that regulates its information flow. The link structures allow for determining which data has to be destroyed for the gates to stay in order. The ILSTM controls and protects cells in equations (8) to (11) by using three gates.

$$e_s = \sigma(\omega_e \times [g_{s-1}, w_s] + a_e) \tag{8}$$

$$j_s = \sigma\left(\omega_j \times [g_{s-1}, w_s] + a_j\right) \tag{9}$$

$$\tilde{D}_s = tanh(\omega_d \times [g_{s-1}, w_s] + a_d) \tag{10}$$

$$D_s = e_s \times D_{s-1} + j_s \times \tilde{D}_s \tag{11}$$

The forget gate determines the number of preceding storage cell states of the ILSTM unit. The input and output gates regulate the storing unit's state using data from input and hidden states, allowing ILSTM temporal connections in long-term classifications.

Dynamic Vortex Search (DVS)

DVS improves the model's capacity to explore a large solution space for optimum financial forecasts by fine-tuning predictions depending on market dynamics. Its exploitation technique detects subtle trends and variations in financial data, which are critical for projecting sustainability. DVS is an optimization technique inspired by the natural dynamics of vortex movements, which are commonly observed in fluid systems such as whirlpools and tornados. DVS is utilized to solve difficult optimization issues by emulating the swirling motion of vortices to explore and settle on the best solution. Equation (12) represents ub as the upper bound of the search space and lb as the lower bound. Equation (13) denotes $D_s(t)$as the state position of the solution at particular time step t during optimization process. $t_1, t_2, t_3, \dots, t_l$denotes the individual time steps undergoes as the vortex optimization method iterates.

$$\mu_0 = \frac{ub-lb}{2} \tag{12}$$

$$D_s(t) = (t_1, t_2, t_3, \dots, t_l) \tag{13}$$

DVS optimization technique is an effective financial forecasting method that crosses vast solution spaces and market trends, leading ultimately to better decision making for sustainability through adaptive and time-evolving solutions.

4. RESULT AND DISCUSSION

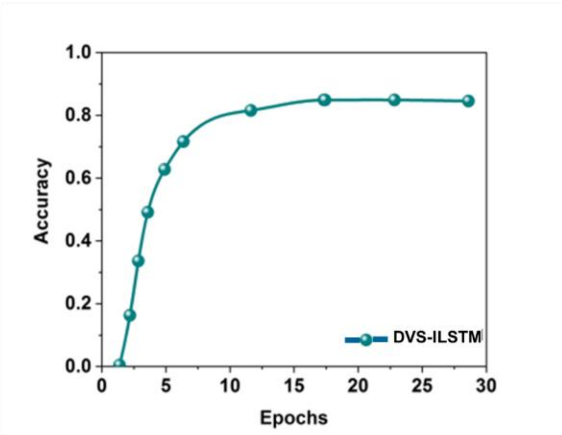
The aim is to improve the decision making in the flower market by using predictive models for better planning and resource management, ultimately assists business increase profits and reduce losses. The necessary protocols were created in a Python 3.11.4 compliant environment. To duplicate the analysis of the recommended optimization choices, a Windows 11 laptop equipped with an Intel i5 11th Gen CPU and 32 GB of RAM is used. DVS-ILSTM method is compared with the existing method, Many-to-Many Long Short-Term Memory with Optuna (MMLSTMOPT) (Chen et al., 2024). The efficiency of DVS-ILSTM is evaluated using RMSE, MAE, R^2 and accuracy training.

Training evaluation

The proportion of accurate forecasts a system makes during the training phase is known as training accuracy. It is computed as the ratio of accurately predicted outcomes to all forecasts. The system's ability to match the training information over time is assessed using training accuracy. Figure 1 represents the training accuracy of the system.

The method's ability to learn from the data over time is shown by the training accuracy. It grows with the integer of epochs, representing that the system gradually gets better at using the training set with an accuracy. This involves that the system retains and adjusts to the particular data it is trained on.

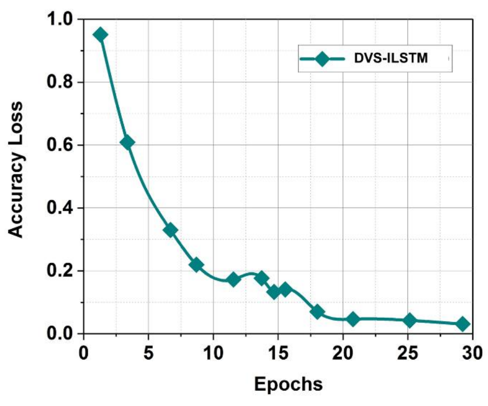
Figure 1: Training accuracy results of the model over Epochs



4.2 Accuracy loss

Accuracy loss is the decline in the accuracy or correctness of a model's predictions or outcomes over time, which is often caused by model deterioration, overfitting, or changes in data distributions. The accuracy loss function of the training data of DVS-ILSTM quantifies the difference between predicted and actual values, guiding model optimization to reduce prediction error. The model's convergence during training is shown by the loss curve, where lower values indicate better performance and diminishing accuracy loss as the epochs are shown in Figure 2.

Figure 2: Accuracy loss outcomes during model training

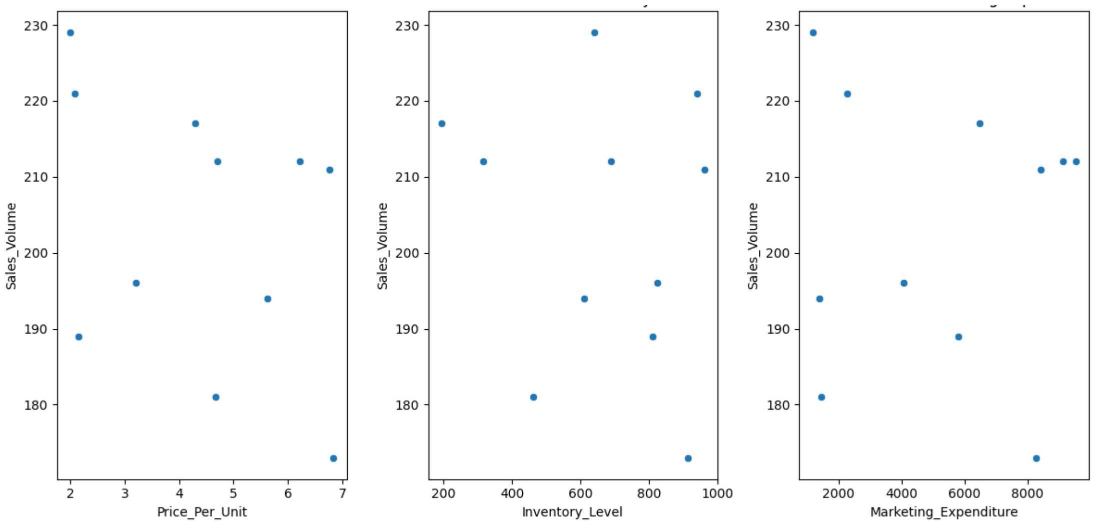


The graph shows the accuracy loss of the DVS-ILSTM model over 30 epochs, starting near 1.0 and decreasing sharply before stabilizing around 0.0. This indicates rapid initial learning and effective convergence, suggesting that the model achieves high accuracy with minimal loss by the final epochs.

4.3 Sales Performance Analysis

Sales performance analysis assesses the success of sales initiatives and identifies important drivers of revenue production. By analyzing sales volume and price per unit, inventory level, and consumer behaviors, it is possible to better understand sales performance, and improve overall financial sustainability in the flower industry. The data driven decisions that increase sales growth, and market competitiveness are crucial. Figure 3 shows the sales performance analysis.

Figure 3: Sales performance outcomes over the evaluation period

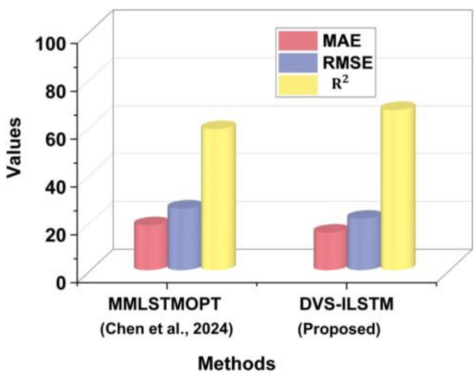


The **marketing expenditure** has the strongest positive correlation with sales volume, suggesting increased spending boosts sales. **Price per unit** shows a weak negative trend, indicating minor price sensitivity. **Inventory level** has no clear impact, implying stock availability doesn't significantly influence sales. Marketing is the key driver of sales growth.

4.4 Comparative analysis

The model's performance is evaluated using various metrics like RMSE, MAE and R^2. It is a measurement of the typical error magnitude between the actual and anticipated values. The MAE is computed by deducting actual values from anticipated values, adding up the absolute values, dividing the outcome by the entire number of remarks and then finding the ethics of the differences. R^2 specifies the frequency of the discrepancy in the FS described by the prediction system. It ranges from zero to one. The RMSE is used to estimate the median magnitude of forecast errors. This is done by squaring the distinctions among the real and biased rates, averaging these errors in squares, and then calculating the square root. Figure 4 and Table 1 show the comparative outcomes of the suggested method and the traditional method.

Figure 4: Comparison outcome of MAE, R^2, and RMSE



The MMLSTMOPT performed moderately with RMSE of 25.79, MAE of 18.81and R^2 of 59. The DVS-ILSTM model outperformed both, with much lower RMSE (21.54) and MAE (15.72), as well as a higher R^2 value (0.67). These findings demonstrate that DVS-ILSTM outperforms existing approach for predictive analytics due to improved accuracy, lower prediction error, and more reliability.

Table 1: Comparative outcome

Models	MAE	RMSE	R^2
MMLSTMOPT (Chen et al., 2024)	18.81	25.79	59
DVS-ILSTM (proposed)	15.72	21.54	67

The aim is to improve the decision making in the flower market by using predictive models for better planning and resource management, which ultimately assists business increase profits and reduce losses. The MMLSTMOPT (Chen et al., 2024) model for financial sustainability of the flower market is characterized by challenges such as increased computational complexity, susceptibility to overfitting because of the highly complex model, as well as dependence on vast, good quality datasets. To overcome this problem, DVS-ILSTM model's accuracy is improved while the risk of overfitting is reduced. Forecasting accuracy has increased with the use of ILSTM in the modeling of temporal dependencies. DVS-ILSTM framework facilitates timely and accurate data-driven decision-making for the financial sustainability of the flower market by interoperating with several types of data sets and effectively handling computational complexity issues.

5. CONCLUSION

The research enhanced flower market decision making by utilizing predictive models for better planning and resource management; it eventually benefits businesses by increasing revenues and reducing losses. This research gathers historical flower market financial trend forecasting data. For pre-processing, a Min-Max Scaling technique was used to normalize the data, ensuring all variables are on the same scale for better model performance. Feature extraction is achieved through ICA, which allowed critical patterns to emerge. This hybrid model supports decisions on production, inventory, and distribution with higher precision. By integrating predictive analytics into operational planning, businesses better manage resources, reduce waste, and enhance profitability. Experimental results displayed improved forecasting performance across RMSE (21.54), MAE (15.72), and R^2 (67%). The proposed approach strengthens strategic planning and contributes directly to the financial sustainability of businesses operating in the competitive flower market. Future research will explore integrating additional data sources to enhance the model's real time forecasting capabilities. Furthermore, it will focus on improving decision-making and financial sustainability across many businesses.

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