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DAIRY FARM SHOP MANAGEMENT SYSTEM (DFSMS) FOR AUTOMATED DAIRY MANAGEMENT

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ABSTRACT

A Dairy Farm Shop Management System (DFSMS) A proposed system to automate the day-to-day activities of the shop, for example, inventory management, sales processing, invoice generation, and reporting. DFSMS is built on the web platform using PHP, MySQL, and JavaScript; therefore, it offers real-time monitoring of perishable goods, which subsequently decreases losses that arise due to spoilage, in addition to human error. This system will provide managers with reports on sales and the status of stock, hence making proper decisions and maximizing the running of the business. The innovation is versatile for future integration with IoT devices for monitoring product conditions and scalability for shop sizes of any size. Index Terms—Automated Dairy Management, Milk Production Moni- toring, Sustainable Dairy Farming, Supply Chain Optimization in Agriculture.

Keywords: Automated Dairy Management, Milk Pro- Duction Monitoring, Sustainable Dairy Farming, Supply Chain Optimization In Agriculture.

I. INTRODUCTION

In the dairy industry, appropriate management of perishable goods means that one would require timely sales and inventory control in order to avoid loss. Traditionally, the manual processes of tracking of inventory, sales, and reporting in the dairy shop pose risks of errors and inefficiency. With emerging advancement in technology, there is a growing tendency to operate under automated systems for operational efficiency and better decision-making capabilities. This paper presents an online management system that helps automate real-time management of dairy shop operations using a combination of inventory tracking, automated sales processing, and advanced reporting. Built with PHP, MySQL, and JavaScript, it reduces spoilage and optimizes stock levels. The system is scalable and adaptable to shops of any size and IoT integration makes it a real game-changer in traditional dairy shop management.

II. METHODOLOGY

A. Data Collection

The first and most crucial step in creating the SARIMA model is to gather data. For instance, historical information on milk consumption or production is accumulated or sourced from either internal documents or records, databases, or ex- ternal data sources. Such data features weekly sales of milk, production volumes, seasonal trends, and external influence Identify applicable funding agency here. If none, delete this. factors that may affect the demand for milk, such as holidays or climatic conditions. Such time series data must be gathered in order to set a basis for SARIMA model forecasting.

B. Data Preprocessing

Once the data has been gathered, preprocessing techniques are carried out on them in order to clean and format it appropriately to prepare them for training a model on the same. These include, Treatment of missing values : missing values might skew prediction. Hence interpolation or imputation methods fill the blank values. Normalization: The data is scaled to have one uniform scale. This may be required if the variables have differing ranges. Feature engineering is the process of incorporating new features into already existing data. This comes in many varieties, such as moving averages, generating lag features, or obtaining seasonal components- say weekly, monthly, or yearly patterns. The goal is raw data conversion into a form that can be fed into the SARIMA model in order to extract all the important trends and patterns found in order to make accurate forecasts.

C. Model Selection

For time series, I use the SARIMA model since it's perfect for seasonal variations. As you would expect, this data of milk demand would mostly present with seasonal variation. Most probably, the milk consumption at some point has certain cycles (e.g., peaks at weekends or during holidays), thus showing seasonal patterns in general. SARIMA would reflect the trend and seasonality by combining the terms: AR (AutoRegressive): This describes how a number of lagged observations relates to an observation. I (Integrated): Differencing the data to make it stationary (remove trends). MA (Moving Average): Picks the relationship between an observation and residual errors from a moving average model applied to lagged observations. Seasonality: SARIMA is the extension of ARIMA in which the seasonal terms capture periodic patterns. It depends on characteristics of the data and special goals of forecasting (here, the weekly demand of milk).

D. Model Evaluation

Model Evaluation After training and validating the model comes the evaluation of the model. The performance of the SARIMA model can be evaluated by using some of the key metrics like following:

RMSE: It is calculated as the average magnitude of the errors between the actual and predicted values, the smaller the value the more accurate it is. MAE: It represents the average of absolute error between the forecasting and real events. R^2 (Coefficient of Determination): Measures how well the model captures the variance in the data, where a value closer to 1 is indicative of a better fit. These metrics ensure that the model works well and upholds the required standards to ensure proper milk demand forecasting.

E. Model Evaluation

After testing and fine-tuning the model, the last thing to do is save a trained SARIMA model to a pickle file. Pickling is a process that serializes the model so it can be saved for later use. The pickle file contains the entire model along with its learned parameters; it can be deployed as is without retraining. This file can now upload to Azure Cloud, allowing it to be used in generating real-time predictions. Such a step ensures that a model can very efficiently be reused so that the Milk Society Portal is able to generate forecasts for weekly demand in milk as new data becomes available.

Generate Pickle File: Once the model is validated and It is saved in a pickle file after evaluation. It is the serialization process of the model so it can be stored and reused without having to rebuild again. The pickle file actually comprises all the parameters and learnt behaviors of the SARIMA model, which makes deployment in a production environment easier.

Azure Cloud Integration: With the model saved as a pickle file, the workflow moves on to the Azure Cloud for deployment:

Register SARIMA Model: The generated pickle file is uploaded and registered on Azure. Setup Custom Environment: The custom environment is set up on Azure to run the model. This environment comprises all the libraries and dependencies needed to run the SARIMA model properly. Deploy Model: Deploy the model on Azure to create a model endpoint or API. Model Endpoint/API: The deployed model is provided as a REST API endpoint such that the external systems, in this case, the Milk Society Portal, can send requests to the model for predictions.

Milk Society Portal: The front end that the user would use in interaction with the model is called the Milk Society Portal. The portal requests the deployed SARIMA model on Azure with a query to the portal asking for the weekly demand in the form of the latest data of milk demand. Response: Milk Prediction The model will process the request, apply the SARIMA-trained model to the given data, and return a prediction to the portal. The user is then presented with a prediction from which he will order appropriate supplies based on his demand forecast in the future. End-to-End Workflow Summary This data collection project pre-processes the data before utilising it for training a SARIMA model to predict the weekly milk. The evaluated model will then be saved as a pickle file and deployed to Azure Cloud. The Milk Society Portal will send requests to the model for the prediction of demand for weekly milk. These predictions are then used to optimize the operations of a firm, diminish wastes, and ultimately make overall efficiency better. This end-to-end workflow shows how seamless integration of machine learning with cloud-based deployment can be done for real- time forecasting in a production environment.

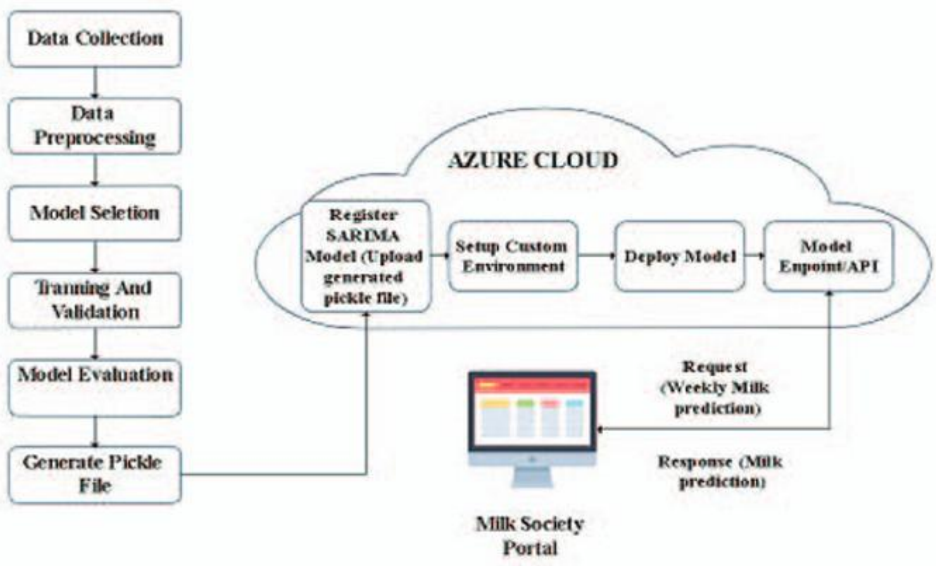

Fig. 1. Project workflow SARIMA model

F. Data Collection

The first step involves collecting data, which is the historical data in regard to milk consumption or production, which was gathered from all the internal records or the databases and external sources which had features such as volume and seasonal trends of selling milk and also any changes in demand for milk possibly caused by holidays or weather. The base of the model is constituted by the collected data since it relies more on the historical time series for SARIMA to make accurate predictions.

G. Data Preprocessing

Preprocessed data, in its raw form, ready to be used in the creation of a model, can contain aspects such as missing value treatment: Missing values in predictions will distort it; to cope, techniques like interpolation or imputation are used to substitute gaps. To have the same scale of data, normalization may be required based on different variables that have vary- ing ranges. Feature engineering: Creating new features from existing datasets, for example, computing a moving average, creating the lag features, or developing seasonal components that may include weekly, monthly, or yearly patterns is part of feature engineering. The purpose is to help transform raw data into a presentable format that can go into the SARIMA model, thus capturing all available trends and patterns for suitable forecasting.

H. Model Selection

The SARIMA model is the best for forecasting time series because it handles data with seasonal variations-very common in milk demand, especially due to trends in consumption, such as increased demand on weekends or certain seasons. SARIMA captures both the trend and seasonality in the data by combining:

AR, AutoRegressive: These capture the relationship be- tween an observation and a number of lagged observations. I (Integrated): Differencing the data to make it stationary. MA: It characterises the association between the realised observation and the realised deviations from the moving-average scheme applied to the realised histories. Seasonality: SARIMA is an extension of ARIMA with seasonal terms to take account of seasonality. The model has been chosen according to the characteristics of the data and the specific goal of the forecast, that is, weekly milk demand.

I. Training and Validation

The next thing to do is train and validate the SARIMA model on the preprocessed data. This involves: Separating the data into two parts: the training and test sets. The model is built from the former, and the latter measures the performance of the model on unseen data. Train a model: Use your training data to fit this model, which should uncover time series patterns or association over time. Validation: At this point, the model is checked against the validation set so that one may see to what extent the model generalizes new data. And the model parameters like p, d, q, P, D, Q, etc are adjusted correspondingly so as to get optimal performance in the forecast.

J. Model Evaluation

Once the model is trained and validated, comes the evalua- tion of the model. Model evaluation evaluates the performance of the SARIMA model based on a set of key metrics like:

RMSE (Root Mean Square Error): Average magnitude of the errors between the predicted and actual values; lower values are better. MAE (Mean Absolute Error): It calculates the average absolute error between predictions and actual outcomes. R^2 (Coefficient of Determination): Measures how well the model captures the variance in the data. This should be close to 1, meaning that a model with a high value indicates a good fit. The above metrics will help in ensuring that the model will perform well and achieve the standards set for good and accurate milk demand forecasting. 6. Create a Pickle File After testing and tuning the model, the final step is to save the trained SARIMA model as a pickle file. Pickling is the process of serializing the model so that it can be stored for later use. The pickle file contains the complete model, along with its learned parameters, which can be deployed without any retraining. This file uploaded to cloud service, say in the context of Azure Cloud. These make real time predictions using them for forecarts. In that manner the model is being reused quite efficiently and its used to predict in subsequent days or weeks such that Milk Society Portal generates weekly forecasts.

This methodology includes the whole process-from data gathering to the final deployment of the SARIMA model for predicting milk, with efficient use of historical data and accurate forecasting capabilities in the Milk Society Portal.

III. CONCLUSION

This methodology describes the entire process from data gathering to deploying the SARIMA model for milk prediction, so as to efficiently use historic data and consequently provide good forecasting capabilities in the Milk Society Portal. Conclusion The Dairy Farm Shop Management System is a true illustration of the full potential in modern dairy farming from all possible digital solutions. Gathering real-time data, handling the inventory more systematically, and keeping detailed records have placed DFSMS as one example of how digitalization could improve the efficiency of an operation, minimize the presence of human error, and ensure profitability in dairy operations. Against the rising demand to have dairy farming more productive and sustainable, its systems like DF- SMS are essential for giving farmers the most appropriate decisions based on fairly accurate data at timely intervals. Not only that these technologies are supportive of economic efficiency, they also improve the welfare of animals through proper health monitoring and resource allocation. Future developments in precision dairy farming, such as IoT-based monitoring and machine learning, will improve predictive capabilities further, so dairy farms will be more resilient and responsive to industry challenges. This research shows that there is a continuous need for innovation in agricultural management systems to create a more sustainable and productive future for the dairy sector.

IV. FUTURE WORKS

AI and Machine Learning: Use deep learning for predictive health and automated decision-making to optimize feeding and milking schedules.

IoT and Edge Computing: Enable low-latency, real-time data processing on-site and integrate advanced sensors for health and milk quality monitoring.

Blockchain: Implement blockchain for secure milk trace- ability and smart contracts for automated transactions.

Big Data Analytics: Apply big data to analyze climate and genetic data for herd management and optimize resource planning with GIS.

AR/VR Applications: Use AR for interactive farm worker training and VR for farm management simulations.

Personalized Recommendations: Provide custom animal care suggestions and tailored dashboards with relevant insights for farmers.

Sustainable Dairy Management: Track carbon footprint, op- timize water use, and manage waste for eco-friendly practices. Advanced Security: Use federated learning for privacy and AI-powered systems to enhance cybersecurity.

Enhanced User Experience: Enable voice commands and multi-language support to improve accessibility.

Regulatory Integration: Automate compliance reporting and recommend available subsidies and grants for farmers.

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