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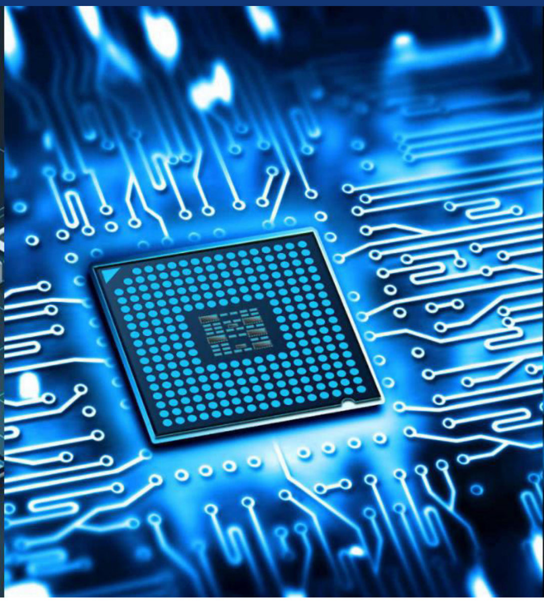


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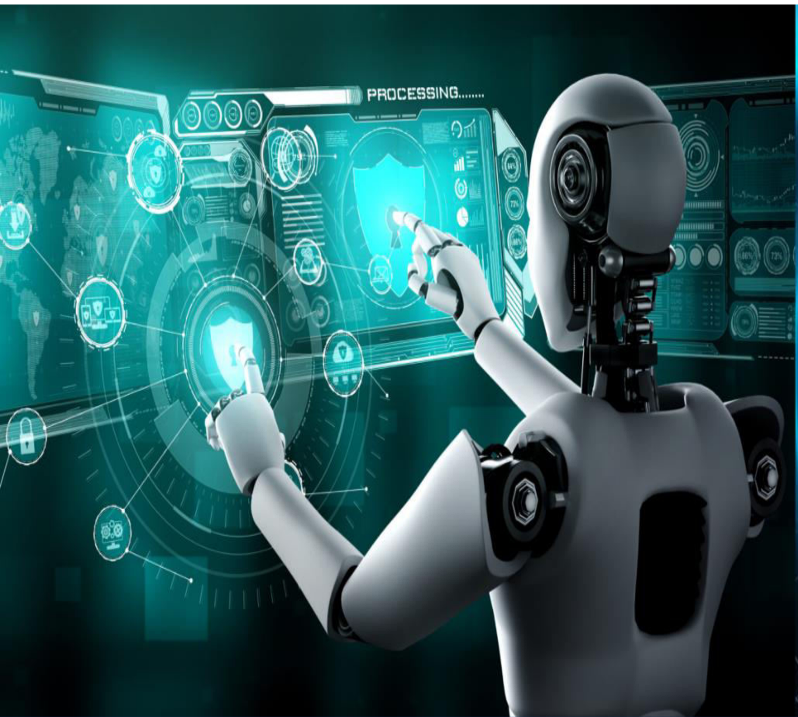

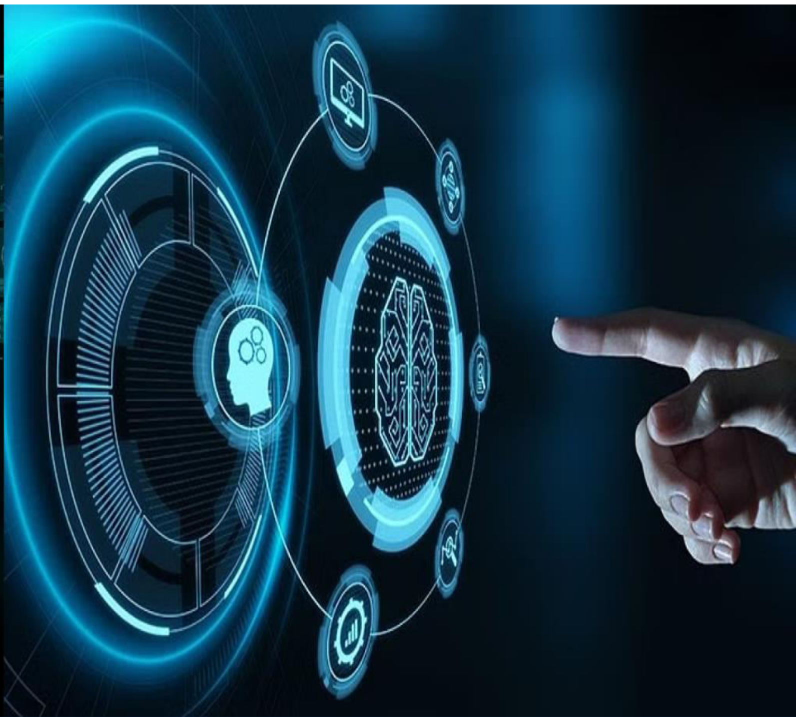

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Machine Learning Strategies for Food Demand Forecasting and Delivery Time Prediction

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ABSTRACT: This paper discusses machine learning techniques used in food demand forecasting and food delivery prediction. Models such as Random Forest, XGBoost, LightGBM, and Gradient Boosting are analyzed. The study also highlights the importance of feature engineering and real-time prediction systems in improving operational efficiency.This paper discusses machine learning techniques used in food demand forecasting and food delivery prediction. Models such as Random Forest, XGBoost, LightGBM, and Gradient Boosting are analyzed. The study also highlights the importance of feature engineering and real-time prediction systems in improving operational efficiency.This paper discusses machine learning techniques used in food demand forecasting and food delivery prediction. Models such as Random Forest, XGBoost, LightGBM, and Gradient Boosting are analyzed. The study also highlights the importance of feature engineering and real-time prediction systems in improving operational efficiency.This paper discusses machine learning techniques used in food demand forecasting and food delivery prediction. Models such as Random Forest, XGBoost, LightGBM, and Gradient Boosting are analyzed. The study also highlights the importance of feature engineering and real-time prediction systems in improving operational efficiency.

I. INTRODUCTION

Food industries face challenges in predicting customer demand and delivery time. Inaccurate predictions lead to food waste, delayed deliveries, and customer dissatisfaction. Machine learning algorithms help improve forecasting accuracy and operational management. This paper reviews modern forecasting methods and delivery prediction systems used in food industries.Food industries face challenges in predicting customer demand and delivery time. Inaccurate predictions lead to food waste, delayed deliveries, and customer dissatisfaction. Machine learning algorithms help improve forecasting accuracy and operational management. This paper reviews modern forecasting methods and delivery prediction systems used in food industries.Food industries face challenges in predicting customer demand and delivery time. Inaccurate predictions lead to food waste, delayed deliveries, and customer dissatisfaction. Machine learning algorithms help improve forecasting accuracy and operational management. This paper reviews modern forecasting methods and delivery prediction systems used in food industries.Food industries face challenges in predicting customer demand and delivery time. Inaccurate predictions lead to food waste, delayed deliveries, and customer dissatisfaction. Machine learning algorithms help improve forecasting accuracy and operational management. This paper reviews modern forecasting methods and delivery prediction systems used in food industries.

II. LITERATURE REVIEW

Traditional statistical models such as ARIMA were initially used for forecasting tasks. However, modern machine learning models like XGBoost, Random Forest, and LightGBM provide better prediction accuracy. Several studies also highlight the role of feature engineering techniques such as lag variables and moving averages.Traditional statistical models such as ARIMA were initially used for forecasting tasks. However, modern machine learning models like XGBoost, Random Forest, and LightGBM provide better prediction accuracy. Several studies also highlight the role of feature engineering techniques such as lag variables and moving averages.Traditional statistical models such as ARIMA were initially used for forecasting tasks. However, modern machine learning models like XGBoost, Random Forest, and LightGBM provide better prediction accuracy. Several studies also highlight the role of feature engineering techniques such as lag variables and moving averages.Traditional statistical models such as ARIMA were initially used for forecasting tasks. However, modern machine learning models like XGBoost, Random Forest, and LightGBM provide better prediction accuracy. Several studies also highlight the role of feature engineering techniques such as lag variables and moving averages.

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Dataset Description

The food demand dataset contains weekly order records, meal details, and fulfillment center information. Delivery datasets include preparation time, traffic conditions, delivery distance, weather, and courier details. These datasets help train machine learning models for accurate prediction.The food demand dataset contains weekly order records, meal details, and fulfillment center information. Delivery datasets include preparation time, traffic conditions, delivery distance, weather, and courier details. These datasets help train machine learning models for accurate prediction.The food demand dataset contains weekly order records, meal details, and fulfillment center information. Delivery datasets include preparation time, traffic conditions, delivery distance, weather, and courier details. These datasets help train machine learning models for accurate prediction.The food demand dataset contains weekly order records, meal details, and fulfillment center information. Delivery datasets include preparation time, traffic conditions, delivery distance, weather, and courier details. These datasets help train machine learning models for accurate prediction.

III. METHODOLOGY

Feature engineering techniques such as lag-based features and EWMA smoothing improve model performance. Machine learning models including Linear Regression, Random Forest, Gradient Boosting, LightGBM, and XGBoost are evaluated using RMSE, MAE, and R2 score metrics.Feature engineering techniques such as lag-based features and EWMA smoothing improve model performance. Machine learning models including Linear Regression, Random Forest, Gradient Boosting, LightGBM, and XGBoost are evaluated using RMSE, MAE, and R2 score metrics.Feature engineering techniques such as lag-based features and EWMA smoothing improve model performance. Machine learning models including Linear Regression, Random Forest, Gradient Boosting, LightGBM, and XGBoost are evaluated using RMSE, MAE, and R2 score metrics.Feature engineering techniques such as lag-based features and EWMA smoothing improve model performance. Machine learning models including Linear Regression, Random Forest, Gradient Boosting, LightGBM, and XGBoost are evaluated using RMSE, MAE, and R2 score metrics.

IV. RESULTS AND DISCUSSION

Random Forest and LightGBM produced better performance compared to traditional regression models. LightGBM showed faster training time with good accuracy. Random Forest performed well in handling non-linear relationships and delivery time prediction.Random Forest and LightGBM produced better performance compared to traditional regression models. LightGBM showed faster training time with good accuracy. Random Forest performed well in handling non-linear relationships and delivery time prediction.Random Forest and LightGBM produced better performance compared to traditional regression models. LightGBM showed faster training time with good accuracy. Random Forest performed well in handling non-linear relationships and delivery time prediction.Random Forest and LightGBM produced better performance compared to traditional regression models. LightGBM showed faster training time with good accuracy. Random Forest performed well in handling non-linear relationships and delivery time prediction.

Limitations

The datasets used in previous studies lack live traffic information, detailed seasonal data, and external factors such as market conditions. Some models also suffer from overfitting issues due to insufficient dataset diversity.The datasets used in previous studies lack live traffic information, detailed seasonal data, and external factors such as market conditions. Some models also suffer from overfitting issues due to insufficient dataset diversity.The datasets used in previous studies lack live traffic information, detailed seasonal data, and external factors such as market conditions. Some models also suffer from overfitting issues due to insufficient dataset diversity.The datasets used in previous studies lack live traffic information, detailed seasonal data, and external factors such as market conditions. Some models also suffer from overfitting issues due to insufficient dataset diversity.

V. FUTURE RESEARCH

Future work should focus on integrating real-time traffic data, weather updates, and deep learning architectures such as transformers. Multi-task learning systems can also improve both demand forecasting and delivery prediction simultaneously.Future work should focus on integrating real-time traffic data, weather updates, and deep learning architectures such as transformers. Multi-task learning systems can also improve both demand forecasting and delivery prediction simultaneously.Future work should focus on integrating real-time traffic data, weather updates, and deep

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learning architectures such as transformers. Multi-task learning systems can also improve both demand forecasting and delivery prediction simultaneously.Future work should focus on integrating real-time traffic data, weather updates, and deep learning architectures such as transformers. Multi-task learning systems can also improve both demand forecasting and delivery prediction simultaneously.

VI. CONCLUSION

Machine learning techniques improve food demand forecasting and delivery prediction accuracy. LightGBM and Random Forest are highly efficient for operational use. Real-time data integration and advanced deep learning models can further improve future systems.Machine learning techniques improve food demand forecasting and delivery prediction accuracy. LightGBM and Random Forest are highly efficient for operational use. Real-time data integration and advanced deep learning models can further improve future systems.Machine learning techniques improve food demand forecasting and delivery prediction accuracy. LightGBM and Random Forest are highly efficient for operational use. Real-time data integration and advanced deep learning models can further improve future systems.Machine learning techniques improve food demand forecasting and delivery prediction accuracy. LightGBM and Random Forest are highly efficient for operational use. Real-time data integration and advanced deep learning models can further improve future systems.

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