**Abstract**

Forecasting models are essential tools for predicting future data trends and optimizing decision-making processes across industries. For non-technical users, utilizing predictive models is often limited by the complexity of setup and interpretation. This paper introduces a Streamlit-based web application designed to allow users to upload datasets, select multiple forecasting models, and compare their outputs in a no-code environment. This tool aims to empower users to identify optimal models without programming expertise. Referring to literature on various demand forecasting methods, it was observed that no single model consistently outperforms others across all contexts, reinforcing the need to experiment with multiple models for optimal results. The study further explores model performance variations under different conditions, highlighting the need for model diversity and adaptability in forecasting.

**Keywords:** Demand Forecasting, Streamlit, Model Selection, Time Series Analysis, Machine Learning

**Introduction**

Forecasting plays a pivotal role in a variety of domains, including retail, healthcare, finance, and manufacturing, where understanding future trends enables organizations to optimize resource allocation, manage supply chains, and meet customer demand effectively. The rapid advancements in data science and machine learning have expanded the range of forecasting techniques available, allowing for greater accuracy in predictions when applied correctly. However, the task of selecting and implementing the appropriate forecasting model remains complex, particularly for non-technical stakeholders who may lack the expertise in data science and coding needed to configure these models.

Traditional forecasting models, such as Autoregressive Integrated Moving Average (ARIMA) and exponential smoothing, have long served as the backbone of time series analysis due to their simplicity and interpretability. These models, though effective in certain stable contexts, often fail to capture complex, non-linear relationships within data—a limitation especially pronounced in dynamic environments with high variability, such as multi-channel retail and healthcare demand forecasting [1][2][3]. To address these limitations, more sophisticated machine learning models like Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks have been developed. These models can handle large, complex datasets and can capture non-linear patterns, making them well-suited for intricate forecasting tasks. However, each model has unique strengths and weaknesses, and no single approach has consistently emerged as the best performer across all forecasting contexts.

A comparative analysis of forecasting models by Mitra et al. (2022) emphasizes the variability in model performance across different datasets and problem domains, advocating for the application of multiple models to better understand their applicability to specific scenarios [2]. In pharmaceutical supply chains, where demand forecasting accuracy is critical due to factors such as regulatory constraints and public health impact, Merkuryeva et al. (2019) demonstrated that hybrid approaches integrating multiple model types could substantially improve forecast accuracy by incorporating both temporal trends and contextual data [3]. This research indicates a strong demand for systems that can evaluate multiple models in parallel, allowing users to identify the most accurate approach for their particular needs. However, current model selection processes often involve complex programming tasks, which are inaccessible to non-technical users, creating a gap between available forecasting technologies and their practical application by stakeholders without coding expertise.

In this paper, we propose a novel solution to bridge this gap through a web-based forecasting application built on Streamlit, a Python-based open-source platform for creating data-driven web applications. This tool is designed to enable users to upload their own datasets, select from various forecasting models—including traditional statistical methods and advanced machine learning algorithms—and visually compare the results, all without the need for programming knowledge. By leveraging this interface, non-technical users can experiment with multiple models and make informed decisions regarding which model best suits their forecasting needs, thus reducing the reliance on technical expertise in the forecasting process. The application offers a user-friendly interface that guides users through the process of uploading data, configuring models, and viewing outputs, making forecasting accessible to business analysts, managers, and other stakeholders who require insights into future trends but may lack the technical knowledge to utilize traditional data science tools.

This study builds on prior literature by addressing the accessibility challenge in predictive analytics. Traditional forecasting platforms typically require either programming skills or substantial customization, which creates a barrier for broader use across industries. While some recent developments in AutoML (automated machine learning) aim to simplify model selection and tuning, these tools often remain inaccessible to non-technical users due to their reliance on coding interfaces and complex configuration options. Furthermore, even when automated, model selection in AutoML platforms is often based on black-box processes that do not offer transparency into how models are chosen, which can reduce user trust and limit the adoption of these tools in decision-making contexts.

By offering a comparative, multi-model approach in a simple, web-based interface, our Streamlit-based application democratizes access to forecasting technology. It provides users with an interactive experience where they can visually examine forecasting results, compare models based on performance metrics, and choose the best fit for their data. Users can experiment with multiple models, including ARIMA, Random Forest, and LSTM, without needing to configure algorithms manually. This flexibility is crucial as it acknowledges that different data characteristics—such as seasonality, trend, and noise—can significantly impact model effectiveness. In line with findings from recent studies, our approach allows users to leverage a diverse model selection, improving the likelihood of identifying a suitable forecasting model for their specific requirements[1][2][3].

The structure of the paper is as follows: Section II reviews related literature on forecasting model performance and discusses the challenges associated with model selection in forecasting. Section III outlines the methodology, detailing the implementation of the web-based application, the model selection options, and the evaluation metrics used to compare model outputs. Section IV presents the experimental setup, including a description of the datasets used to validate the application’s performance. Section V provides results and discusses the implications of the multi-model approach for non-technical users. Finally, Section VI concludes the paper and suggests directions for future work, including potential expansions of model selection options and improvements in user guidance for non-technical stakeholders.

**Literature Review**

In the field of demand forecasting, traditional statistical models like ARIMA and exponential smoothing have long been used. These models are known for their simplicity and interpretability but often fall short with complex datasets that exhibit non-linear patterns (referance paper 1). Machine learning models, including Random Forest, XGBoost, and neural networks, offer advanced capabilities for capturing intricate relationships within data but can be computationally intensive and require careful tuning (referance paper 2). Comparative studies, such as those by Mitra et al. (2022) and Merkuryeva et al. (2019), highlight the trade-offs between traditional and machine learning approaches, with the latter generally outperforming in contexts involving large and varied datasets (referance paper 2) (referance paper 3).

Several recent studies emphasize hybrid approaches, combining strengths of different models. For example, Punia et al. utilized a hybrid model combining LSTM and Random Forest, achieving significant gains in forecast accuracy by leveraging LSTM’s ability to capture temporal dynamics and Random Forest’s robustness to fluctuations (referance paper 2). In the pharmaceutical industry, where demand forecasting accuracy is critical, Merkuryeva et al. applied multiple regression and symbolic regression to incorporate contextual factors like price and economic indicators, improving the model’s responsiveness to external changes (referance paper 3).

Despite advances, a universal model that performs optimally across all datasets has not emerged. Studies consistently reveal that no model consistently outperforms others across diverse forecasting environments, reinforcing the need to evaluate multiple models for a given task. This paper builds on these findings by developing a tool that democratizes model experimentation, empowering users to make informed model selections without requiring technical expertise. The proposed web application bridges this gap by offering non-technical users a simplified interface to compare model outputs and select the best fit based on their data.