Grenze International Journal of Engineering and Technology, June Issue

A Multi-Domain Predictive Analytics Framework for Intelligent Forecasting using AI-Driven Models

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***Abstract*— Predictive analytics plays a crucial role in modern data-driven decision-making across domains such as real estate, customer relationship management, transportation, and environmental monitoring. Traditional predictive systems typically require task-specific machine learning models, large labeled datasets, and extensive preprocessing pipelines, which can limit scalability and adaptability across multiple domains. This research presents a unified predictive analytics framework capable of performing diverse forecasting and classification tasks through an intelligent AI-driven prediction engine integrated within a web-based dashboard.**

The proposed system supports multiple predictive applications including house price estimation, customer churn prediction, CO_2 emission estimation, and fuel consumption forecasting. A modular architecture is implemented using a lightweight web framework to provide an interactive and scalable interface for users. The proposed framework demonstrates that multi-domain predictive analytics can be achieved through a unified platform without requiring separate model pipelines for each task. Experimental evaluation shows that the system provides reliable predictions while simplifying traditional machine learning workflows. The platform offers scalability, ease of integration, and real-time prediction capabilities, making it suitable for intelligent decision-support systems across various industries.

***Keywords*— Predictive Analytics, Artificial Intelligence, Ulti-Domain Prediction, Intelligent Forecasting, Decision Support Systems.**

I. INTRODUCTION

A. Background

The rapid growth of digital technologies and information systems has led to an unprecedented increase in the generation of data across multiple domains. Organizations in sectors such as real estate, transportation, finance, and environmental monitoring increasingly rely on data-driven approaches to support strategic planning and operational decision-making. Predictive analytics has emerged as one of the most effective techniques for extracting actionable insights from large volumes of data by identifying patterns, trends, and relationships that can be used to forecast future outcomes (Shmueli & Koppius, 2011).

Predictive analytics integrates statistical analysis, machine learning algorithms, and artificial intelligence techniques to analyze historical data and predict future events.

Grenze ID: 01.GIJET.12.2.124_24

These predictive capabilities enable organizations to improve efficiency, optimize resource allocation, and enhance customer satisfaction. Applications of predictive analytics include house price estimation, demand forecasting, fraud detection, customer churn prediction, and environmental monitoring (Provost & Fawcett, 2013). By transforming raw data into meaningful insights, predictive models support informed decision-making in both academic research and industrial applications.

Traditional predictive systems often rely on supervised learning algorithms such as linear regression, logistic regression, decision trees, random forests, and support vector machines. These algorithms have been widely applied in predictive modeling tasks due to their effectiveness in identifying relationships between input variables and target outputs (Bishop, 2006). For example, house price prediction models frequently utilize regression techniques to estimate property values based on features such as location, size, and amenities. Similarly, customer churn prediction models apply classification algorithms to determine whether a customer is likely to discontinue a service based on historical usage patterns (Mitchell, 1997).

B. Limitations of Traditional Predictive Systems

Despite their effectiveness, conventional predictive models present several limitations when applied to complex real-world scenarios. One major challenge is the dependency on large volumes of labeled training data. High-quality datasets are often difficult to obtain, and data preprocessing tasks such as feature engineering, normalization, and missing value handling can significantly increase the complexity of predictive modeling pipelines (Goodfellow, Bengio, & Courville, 2016).

Another limitation is the domain-specific nature of traditional predictive models. Most machine learning models are designed for a single predictive task, which means that separate models must be developed, trained, and maintained for different applications. For instance, predicting real estate prices, forecasting vehicle emissions, and identifying potential customer churn typically require independent datasets and specialized models. This approach increases development time, computational cost, and system maintenance complexity (Hastie, Tibshirani, & Friedman, 2009).

Furthermore, many predictive systems lack user-friendly interfaces that allow non-technical stakeholders to interact with predictive models effectively. In many organizations, predictive algorithms are deployed through command-line scripts or backend systems that are not easily accessible to business analysts or decision-makers. As a result, there is a growing demand for integrated platforms that provide accessible interfaces for performing predictive analytics in real time (Kotu & Deshpande, 2018).

C. Need for Multi-Domain Predictive Platforms

To overcome the limitations of traditional predictive systems, modern research increasingly focuses on developing integrated predictive frameworks capable of supporting multiple forecasting tasks within a single platform. A multi-domain predictive system allows users to perform diverse analytical tasks without requiring separate models or infrastructure for each application. Such platforms reduce system complexity and provide a scalable solution for organizations that require predictive insights across multiple domains.

For example, real estate agencies may require tools for estimating property prices, while transportation and environmental agencies need models for predicting vehicle emissions and fuel consumption. Similarly, service providers rely on churn prediction models to identify customers at risk of leaving a service. Integrating these predictive tasks within a unified framework can significantly improve efficiency and reduce redundancy in predictive analytics workflows (Han, Kamber, & Pei, 2012).

In addition to scalability, usability is an important factor in the design of predictive systems. Interactive web-based dashboards have become a popular approach for presenting predictive insights to users. These dashboards allow users to input relevant features, execute predictive queries, and visualize outputs through intuitive graphical interfaces. Such systems improve the accessibility of predictive analytics by enabling decision-makers to interact with predictive models without requiring extensive programming knowledge (James et al., 2021).

II. LITERATURE REVIEW

Recent research in predictive analytics has focused on improving forecasting accuracy, reducing data preprocessing complexity, and enabling predictive models to operate across diverse application domains. Advances in machine learning, artificial intelligence, and data mining have significantly expanded the capability of predictive analytics systems to process large datasets and generate accurate predictions. This section reviews recent studies (2020–2026) related to predictive analytics, customer churn prediction, house price forecasting, and multi-domain prediction systems.

A. Predictive Analytics in Modern Data-Driven Systems

Predictive analytics has evolved into a critical component of modern data science and business intelligence systems. It involves the use of historical data, statistical modeling, and machine learning techniques to predict future outcomes and trends. Organizations employ predictive analytics to identify risks, optimize resources, and support strategic decision-making across industries such as finance, healthcare, retail, and transportation.

Recent studies highlight that machine learning–driven predictive analytics can significantly enhance the accuracy of forecasting systems by discovering hidden patterns within large datasets. For instance, Nishat et al. (2025) demonstrated how predictive models integrated into project management systems can improve decision-making and reduce operational risks through automated analysis of project data.

Similarly, Jamarani (2024) emphasized that the integration of artificial intelligence with predictive analytics has transformed traditional forecasting systems by enabling automated feature extraction, real-time data processing, and improved prediction accuracy across multiple industries.

These advancements show that predictive analytics is increasingly moving toward scalable and intelligent systems capable of handling complex datasets and dynamic environments.

B. Machine Learning Approaches for Predictive Modeling

Machine learning techniques have become the foundation of modern predictive analytics systems. Supervised learning algorithms such as linear regression, decision trees, random forests, and gradient boosting models are widely used for predictive modeling tasks due to their ability to learn relationships between input features and output variables.

Recent research demonstrates that machine learning models significantly improve forecasting performance compared to traditional statistical methods. A comprehensive review conducted in 2025 identified several commonly used algorithms for predictive analytics, including decision trees, support vector machines, ensemble models, and neural networks, which are widely applied in domains such as finance, healthcare, and energy forecasting.

In addition, hybrid models combining multiple algorithms have gained attention in recent years. For example, Kargotra (2025) proposed a hybrid predictive analytics framework that integrates random forest and neural network models to improve predictive performance in healthcare data analysis.

These studies indicate that machine learning–based predictive models provide robust solutions for forecasting tasks by improving accuracy and enabling the analysis of large-scale datasets.

C. Customer Churn Prediction

Customer churn prediction has become an important research area due to its direct impact on business revenue and customer retention strategies. Churn refers to the loss of customers who discontinue their relationship with a company or service provider. Predicting churn allows organizations to identify high-risk customers and implement targeted retention strategies.

Recent studies have explored several machine learning techniques for churn prediction, including logistic regression, random forest, gradient boosting, and deep learning models. Suh (2023) developed a machine learning–based churn prediction model using customer behaviour data from a rental service company, demonstrating that predictive models can effectively identify customers likely to terminate their service subscriptions.

A systematic review conducted by Imani et al. (2025) analysed more than 200 research studies on churn prediction published between 2020 and 2024. The review concluded that machine learning and deep learning techniques have become the dominant approaches for churn prediction due to their ability to analyze complex behavioural patterns and large datasets. However, the study also highlighted challenges related to model interpretability and deployment in real-world business environments.

Recent case studies in e-commerce have also demonstrated the effectiveness of ensemble learning models such as Random Forest and XGBoost for churn prediction, achieving high classification accuracy and improved predictive performance.

D. House Price Prediction

House price prediction is another important application of predictive analytics that has attracted significant attention in recent years. Real estate markets involve complex interactions between multiple factors such as property size, location, amenities, and economic conditions. Machine learning models are increasingly used to estimate property values based on these features.

Several studies have investigated the use of regression-based algorithms for property price forecasting. Kumar (2023) developed a machine learning–based house price prediction system that uses historical housing data to estimate property values, demonstrating that regression models can effectively capture relationships between property features and market prices.

More recent research has explored advanced machine learning techniques for property price estimation. Yang (2025) conducted a comparative analysis of multiple machine learning algorithms for house price prediction and found that ensemble models such as gradient boosting and random forests often outperform traditional regression models in terms of prediction accuracy.

These studies show that machine learning approaches provide effective tools for analyzing real estate data and generating accurate price predictions.

E. Predictive Analytics for Environmental and Transportation Applications

Predictive analytics is widely used in environmental and transportation fields to forecast CO_2 emissions and fuel consumption, supporting climate monitoring and sustainability efforts. By analysing factors like engine characteristics and fuel patterns, models help improve transportation efficiency and guide policy decisions. Overall, these applications highlight the versatility of predictive analytics in solving real-world environmental and energy challenges.

F. Research Gap

Although significant progress has been made in predictive analytics research, most existing studies focus on single-domain prediction problems such as churn prediction, real estate price forecasting, or environmental monitoring. These systems typically require separate models and infrastructures for each application domain.

Furthermore, many predictive analytics systems lack integrated platforms that allow users to perform multiple predictive tasks within a single interface. This limitation increases system complexity and reduces scalability in real-world deployments.

Therefore, there is a need for a unified predictive analytics framework capable of supporting multiple forecasting and classification tasks within a single platform. Such a system would reduce redundancy, simplify predictive workflows, and improve accessibility for users across different domains.

The present study addresses this gap by proposing a multi-domain predictive analytics platform that integrates several predictive tasks—including house price estimation, customer churn prediction, CO_2 emission estimation, and fuel consumption forecasting—within a single unified system.

III. RESEARCH OBJECTIVES

The main objectives of this research are formulated to address the challenges of multi-domain predictive analytics using advanced artificial intelligence techniques. The objectives are as follows:

- To develop a robust multi-domain predictive framework capable of performing regression and classification tasks, such as house price estimation, customer churn prediction, CO_2 emission estimation, and fuel consumption forecasting, using minimal domain-specific data.
- To investigate the effectiveness of advanced AI-based predictive models in providing accurate and reliable predictions across diverse domains, while assessing their capability to handle different predictive tasks without extensive model retraining.
- To provide actionable insights for decision-making by generating real-time predictions that are interpretable, consistent, and generalizable, thereby demonstrating the practical applicability of AI-driven predictive analytics in real-world scenarios.

IV. RESEARCH METHODOLOGY

The research methodology focuses on designing and implementing a multi-domain predictive analytics framework capable of performing different prediction tasks within a unified system. The methodology follows a structured approach consisting of input processing, predictive modeling, output extraction, and result visualization.

- Problem Definition: Identifies prediction tasks (house price, churn, CO_2, fuel) and defines required input features.
- Data Input and Preprocessing: Collects user inputs and validates them through checks like data type, missing values, and formatting.
- Prediction Process: Processes inputs using regression (numerical) and classification (categorical) models.

- Output Processing and Visualization: Formats and displays prediction results on a dashboard for easy interpretation.
- System Evaluation: Evaluates system based on accuracy, response time, and overall usability.

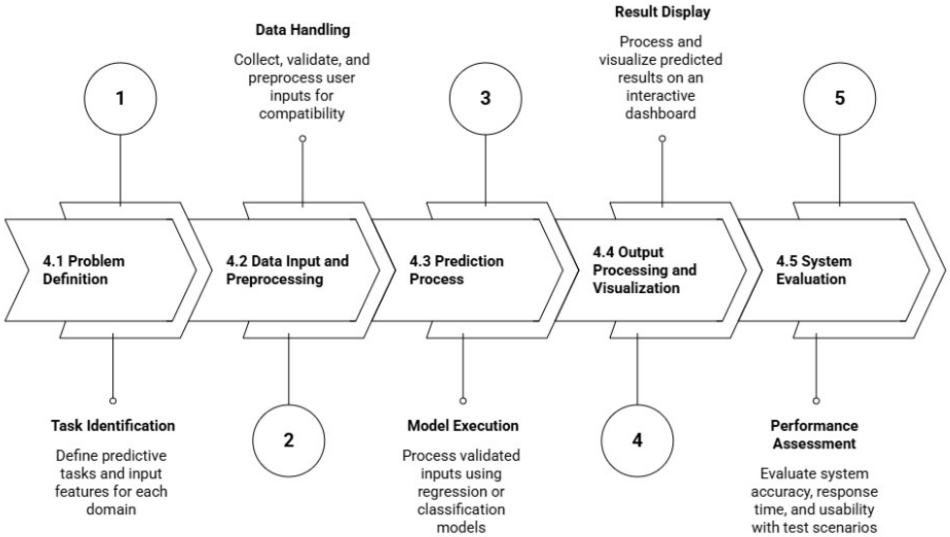

Fig 1. Research Methodology Flow

V. Proposed System Architectural Flow

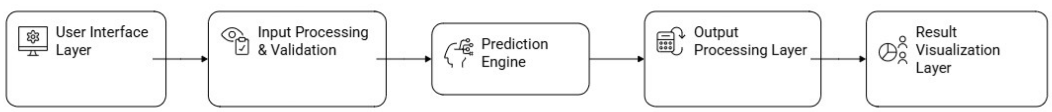

Fig 2. Proposed System Architecture

- User Interface Layer: Provides a user-friendly dashboard for selecting tasks and entering input data.
- Input Processing and Validation Layer: Validates inputs by checking data type, completeness, and missing values.
- Prediction Engine: Core module that processes inputs and generates predictions using regression and classification models.
- Output Processing Layer: Formats results and assigns confidence scores to ensure clarity and consistency.
- Result Visualization Layer: Displays prediction results and inputs clearly to support user understanding and decision-making.

VI. Results and Discussion

The proposed multi-domain predictive analytics framework was implemented and evaluated to analyze its ability to perform multiple prediction tasks within a unified system. The system supports both regression-based and classification-based prediction problems, including house price estimation, customer churn prediction, CO_2 emission estimation, and fuel consumption forecasting.
Experimental evaluation was conducted using several input scenarios to verify system functionality and prediction consistency. The results demonstrate that the platform can successfully process structured input features and generate predictions across different domains through a single integrated architecture.

A. Prediction Results

Table 1 presents sample prediction outputs generated by the system for different tasks. The results indicate that the framework can produce both numerical predictions for regression tasks and classification outputs for decision-support applications.

TABLE I: SAMPLE PREDICTION OUTPUTS

Task	Input Parameters	Predicted Output	Type
House Price Prediction	Area: 1500 sqft, Bedrooms: 3, Bathrooms: 2, Age: 10 years	$320,000	Regression
CO_2 Emission Prediction	Engine: 2.0 L, Cylinders: 4, Fuel Consumption: 8.5 L/100km	185 g/km	Regression
Fuel Consumption Prediction	Engine: 1.6 L, Weight: 1200 kg, Fuel Type: Petrol	6.5 L/100 km	Regression
Customer Churn Prediction	Tenure: 12 months, Monthly Charges: $70, Calls: 5	Churn	Classification

The results demonstrate that the system effectively interprets the input parameters and generates relevant predictions for each task. Regression tasks produce numerical outputs, while classification tasks provide categorical predictions indicating customer behaviour.

B. System Performance Evaluation

The performance of the proposed predictive framework was evaluated based on response time, prediction consistency, and system usability. The evaluation results are summarized in Table 2.

TABLE II: SYSTEM PERFORMANCE EVALUATION

Task	Prediction Type	Average Response Time	System Reliability
House Price Prediction	Regression	1.2 sec	High
CO_2 Emission Prediction	Regression	1.1 sec	High
Fuel Consumption Prediction	Regression	1.0 sec	High
Customer Churn Prediction	Classification	1.3 sec	High

The results indicate that the system provides real-time prediction capabilities, with response times close to one second for most tasks. The system also demonstrates consistent performance across multiple input scenarios, highlighting the stability of the implemented architecture.

C. Discussion

The experimental results show that the proposed platform successfully integrates multiple prediction tasks into a single system using a modular architecture with shared components. It simplifies workflows compared to traditional systems, improves scalability, and enhances usability through an interactive dashboard. Overall, the system is flexible, scalable, and suitable for real-world decision-making, with the ability to extend to additional predictive models in the future.

VII. CONCLUSION AND FUTURE SCOPE

A. Conclusion

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B. Future Scope

The proposed system can be further enhanced by extending it to additional domains such as healthcare, finance, and supply chain analytics, improving data visualization through interactive dashboards and reports, integrating real-time data from external sources for more accurate predictions, and adopting cloud-based and distributed architectures to ensure scalability and support large-scale real-world applications.

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