EXPLAINABILITY: PREDICTION OF THE NUMBER OF FIRE INCIDENTS IN DUBLIN

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Increased urbanization and industrial activity are leading to the **frequency of fire incidents,** which causes significant damage to **life and property** and increases **social and economic costs.** This study presents a comparative analysis of seven machine learning models for predicting fire incidents in Dublin. Utilizing various regression techniques, including **Prophet, ARIMA, Random Forest Regression, and others**, the research evaluates the performance of each model based on metrics like Mean Squared Error (**MSE**), Mean Absolute Error (**MAE**), Mean Absolute Percentage Error (**MAPE**) and **R-Squared** scores. The **Prophet model emerged as the most effective with a high R-Squared score of 0.92,** enabling accurate predictions of fire incidents in Dublin for the next 2 years. Furthermore, the study underscores the **importance of Explainable AI (XAI)** in enhancing the **transparency** and **understanding** of these technologies. By focusing on data transparency, model explainability, and effective visualizations, the study aims to make AI models more comprehensible and trustworthy, especially in domains with significant social impact. This approach not only advances the field of AI but also provides valuable insights for urban planning and emergency response strategies in Dublin.

Research Question 1

Which model has the best performance for predicting time series data?

Research Question 2

What time period exhibits the most distinct seasonality for prediction?

Research Question 3

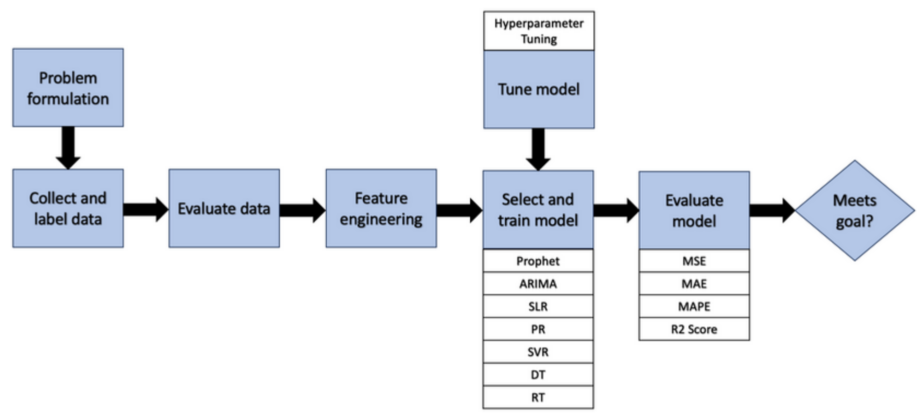
How can the AI project be made explainable for users?

INTRODUCTION

Urbanization and industrial activities in Dublin have led to an increase in fire incidents, posing risks to life, property, and the environment. This study **aimed to predict fire incidents in Dublin using various regression models and enhance their transparency through Explainable AI (XAI)**. The **Prophet model** initially **performed the best**, and after tuning, its performance improved. These models can aid urban planning, emergency response, and city risk management. **XAI aims to make AI decisions understandable to humans, bridging the gap between AI reasoning and human decision-making**, especially in critical applications. This study integrates XAI to provide interpretable reasons for predictions, making AI transparent and accountable. The study covers related works, methodology, experimental results, and future research directions.

METHODOLOGY

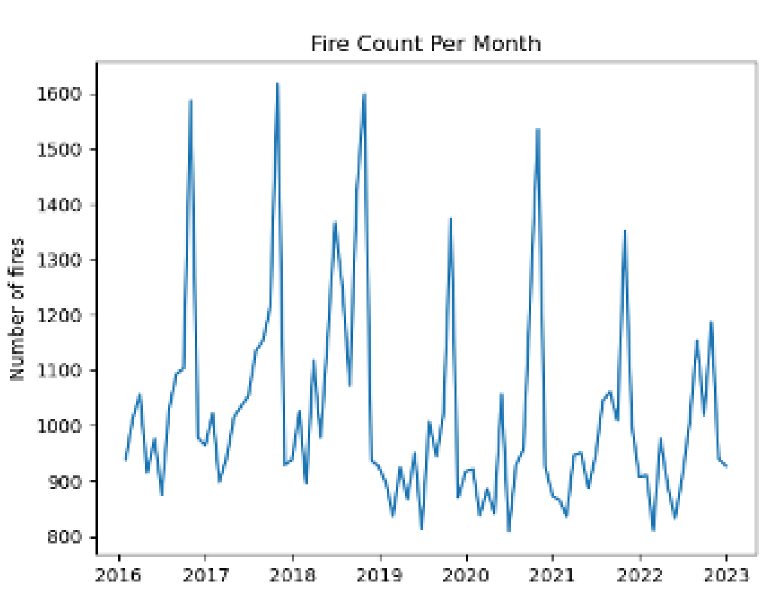
This study used a **machine learning pipeline** to analyze fire incident data in Dublin and compared the performance of **seven models: Prophet, ARIMA, simple linear regression, polynomial regression, support vector regression, decision tree regression, and random forest regression**. The goal was to **predict the number of fire incidents in Dublin** and **provide actionable insights** for the Dublin Fire Brigade and the city. Here's a concise summary of the methodology:

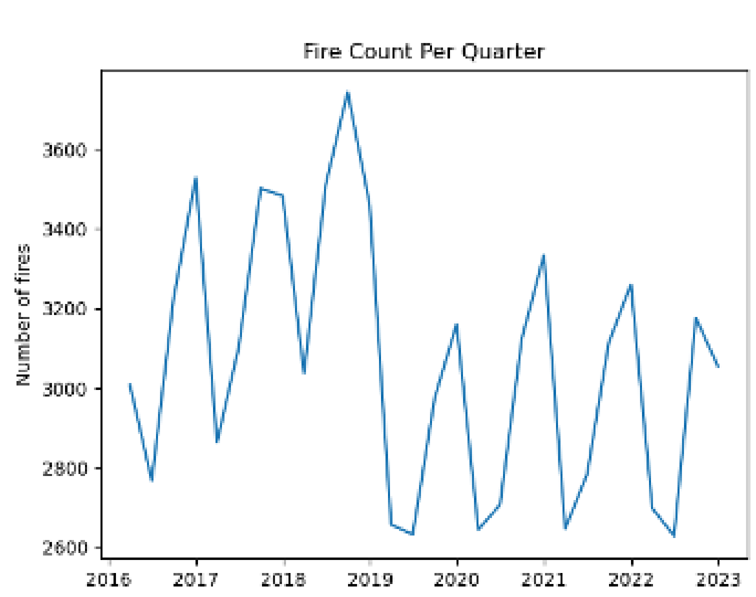


1. **Problem Formulation**: The study aimed to **predict fire incidents in Dublin**, addressing the challenges posed by increasing urban density and complexity.
2. **Collect and Label Data**: Data was **sourced from Smart Dublin**, providing detailed logs of annual incident activities recorded by the Dublin Fire Brigade.
3. **Evaluate Data**: The dataset included **85,813 entries** with features like date, station name, and incident details. Some columns had missing values.
4. **Feature Engineering**: The 'Date' column was converted into a **datetime object,** and **time-related features** like day of the week, month, and year were extracted. **Outliers** were considered and not removed as they might be part of the time series pattern.
5. **Select and Train Model**: Different models were considered, including **Prophet, ARIMA, linear regression, polynomial regression, support vector regression, decision tree regression, and random forest regression**. The data was split into a **training set (80%) and a test set (20%) to preserve the time order.**
6. **Evaluate Model**: Model performance was evaluated using metrics like Mean Squared Error (**MSE**), Mean Absolute Error (**MAE**), Mean Absolute Percentage Error (**MAPE**), and **R-Squared scores**. The Prophet model performed best, especially after tuning its hyperparameters.
7. **Tune Model**: The Prophet model's hyperparameters were tuned, including **changepoint_prior_scale**, **seasonality_prior_scale**, **holidays_prior_scale**, and **seasonality_mode**, to improve accuracy.

SEASONALITY ANALYSIS

Time series data exhibit patterns over time, where data from earlier time points can influence data at later time points. Many time series data show seasonality (e.g., annual, monthly, weekly patterns) or trends (e.g., tendencies to increase or decrease over time). As seen in below graphs, **in this dataset, Seasonality can be observed in time period of monthly and quarterly.**



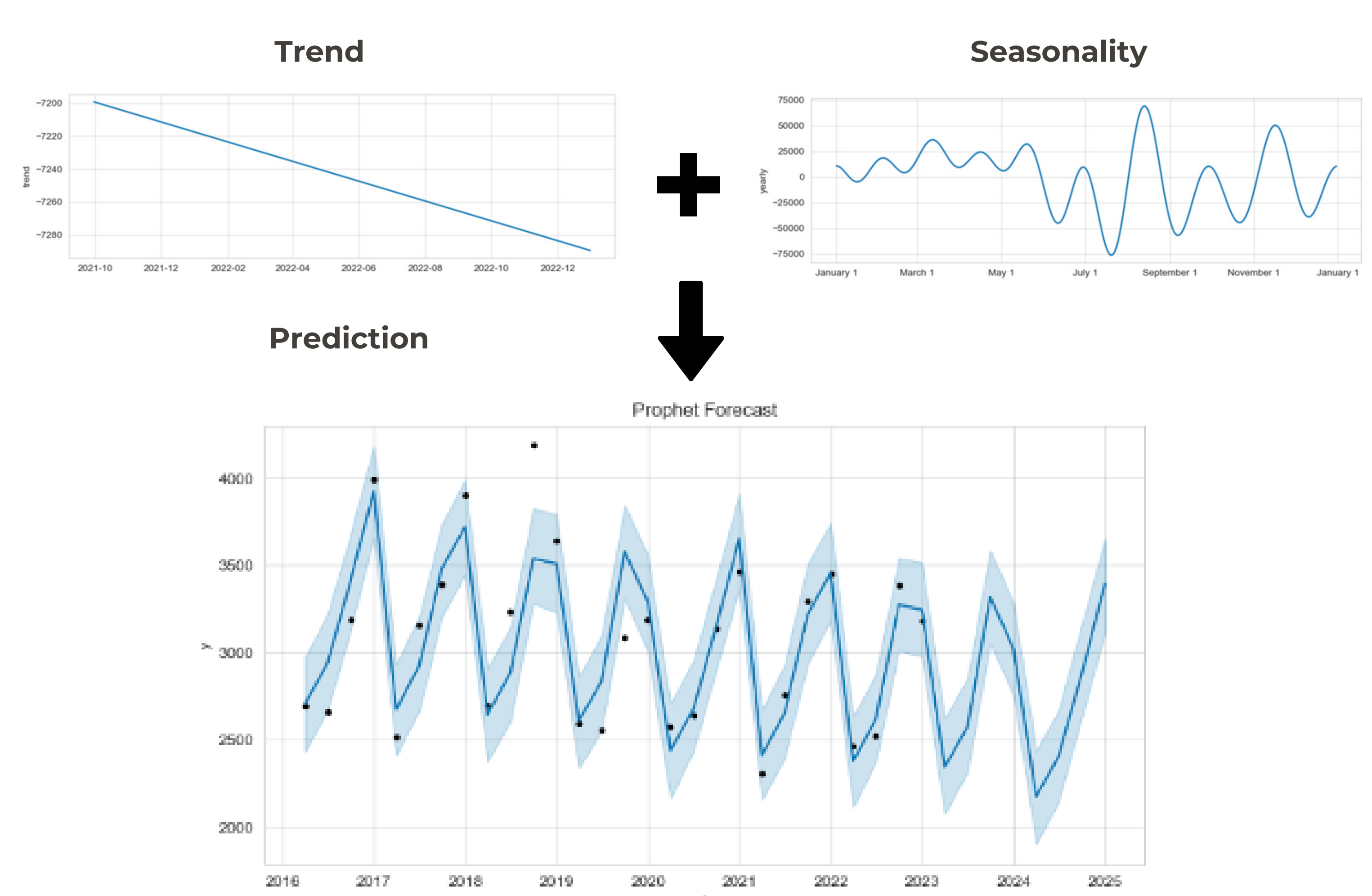


EXPLAINABLE AI (XAI) WITH PROPHET

Trend: The trend component captures the **long-term progression of the data**. A **linear decreasing trend** was observed in this dataset, indicating that the model has detected a **long-term downward trend** in the variable over time. This trend is modeled using piecewise linear regression, allowing flexibility in fitting the trend to the data.

Seasonality: The seasonality component represents **regular patterns of change**, such as yearly or weekly fluctuations. **Variations illustrate how the metric changes at specific times of the year.** The prediction model utilizes this pattern to estimate future seasonal variations.

Prediction: The **trend and seasonality graphs mentioned above are components of the Prophet model's output**, illustrating how the model has analyzed the data to make predictions. **The trend graph reveals the model's prediction of the overall direction** the data is heading over time. **The seasonality graph demonstrates yearly patterns**, indicating recurring variations throughout the year. **The final forecast is a combination of these components.**



This XAI-driven analysis provides **insights into how the Prophet model generates predictions** by **considering trends, seasonality, and historical patterns in the data**. It helps make the model's decision-making process more **transparent** and **understandable**, which is crucial in applications with significant social impact.

Quarterly Prediction 2023 - 2024

Date	**31/03/2023**	**30/06/2023**	**30/09/2023**	**31/12/2023**
Count	2,343	2,569	3,313	3,023
Date	**31/03/2024**	**30/06/2024**	**30/09/2024**	**31/12/2024**
Count	2,174	2,408	2,882	3,390

Monthly Prediction 2023 - 2024

Date	**31/01/2023**	**28/02/2023**	**31/03/2023**	**30/04/2023**	**31/05/2023**	**30/06/2023**
Count	859	803	918	875	925	936
Date	**31/01/2024**	**29/02/2024**	**31/03/2024**	**30/04/2024**	**31/05/2024**	**30/06/2024**
Count	863	802	917	880	932	941
Date	**31/07/2023**	**31/08/2023**	**30/09/2023**	**31/10/2023**	**30/11/2023**	**31/12/2023**
Count	1,021	1,030	1,097	1,448	963	884
Date	**31/07/2024**	**31/08/2024**	**30/09/2024**	**31/10/2024**	**30/11/2024**	**31/12/2024**
Count	1,024	1,032	1,090	1,452	972	884

CONCLUSION

Q1. Which model has the best performance for predicting time series data?

- The study found that **time series models** outperformed general regression models when predicting time series data. Among the time series models evaluated, the **Prophet** model demonstrated the highest prediction accuracy and reliability.

Q2. What time period exhibits the most distinct seasonality for prediction?

- The analysis of the dataset revealed that the quarterly time period exhibited the most distinct and prominent seasonality patterns.

Q3. How can the AI project be made explainable for users?

- To ensure the AI project's explainability for users, the following strategies can be adopted:
  - **Data Transparency**: Provide clear information about the data sources and preprocessing steps, including data collection methods and transformations applied. Users should have a transparent understanding of the data.
  - **Model Explainability**: Enhance the interpretability of the Prophet model by making it more transparent. This was achieved by showcasing **trend and seasonality graphs that illustrated the prediction process**. These improve the model's explainability, enabling users to understand its workings without relying on complex analysis techniques.
  - **Visualizations**: Utilize visual aids to convey how the model operates. Create visualizations that display historical data, observed patterns, and the model's predictions. Highlight key trends, seasonality, and anomalies captured by the model.