Analyzing Fire Response Times, Water Usage, and Incident Type Predictability in Izmir

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***Abstract*—The increasing frequency and severity of fires around the world highlights the urgent need for a detailed examination of key fire response metrics. The research will analyse the 'Izmir 2023 Fire Response Statistics' to investigate three critical questions: whether there are significant differences in average response times across various fire types; the extent of variability in water usage among different fire categories; and the feasibility of predicting fire incident types. The findings aim to provide insights that can inform predictive modelling and resource allocation for more effective fire management.**

***Index Terms*—Average Response Time, Water Usage, Fire Type Classification, Predictive Modeling, Fire Incidence Prediction**

I. Introduction

The increasing frequency and severity of fires around the world highlights the need for a more in-depth understanding of key fire response metrics, particularly average response time and water usage across different fire types. This research will address three critical questions: are there significant differences in average response times for various fire types? What is the extent of variability in water usage among different fire categories? And, is it feasible to predict fire incident types? To investigate these questions, this study will analyze the 'Izmir 2023 Fire Response Statistics' dataset. Furthermore, a review of relevant literature will provide essential context for these primary inquiries, helping to inform aspects such as predictive modelling and resource allocation. While these existing studies offer foundational insights, they will not be the sole basis for the current investigation.

For instance, a recent study by Ku and Liu, published in the journal Fire in 2024 and titled "Predictive Modeling of Fire Incidence Using Deep Neural Networks," details the development of a deep neural network (DNN) model for forecasting fire occurrences in Keelung City, Taiwan. Their research, reporting a high coefficient of determination ($R^2 = 0.89$), underscores the value of incorporating diverse data types. Specifically, they integrated demographic, architectural, and economic factors into their predictive framework. Such an approach, utilizing multidimensional data for feature selection and classification in fire prediction, aligns well with broader strategies for comprehensive risk assessment. The study also explored how different urban renewal strategies impact fire incidence, emphasizing the significant role of economic factors [1].

Other research has focused on comparing machine learning and time series approaches for predictive modeling of urban fire incidents, using Austin, Texas, as an example. These studies typically examine the effectiveness of models like Random Forest and ARIMA in predicting fire occurrences, taking into account the influence of different fire types and urban district characteristics. Analyses from such studies indicate that time series models like ARIMA generally tend to excel in predicting most fire types. However, there are exceptions where machine learning models such as Random Forest may be more suitable (for instance, for auto fires). Furthermore, this line of research highlights significant differences in model performance across various urban districts, suggesting that local features considerably influence fire incidence prediction. This, in turn, underscores the importance of tailoring predictive models to both specific fire types and local urban dynamics for more effective fire risk management and resource allocation [2].

Another relevant contribution is a recent preprint where researchers utilized machine learning techniques to analyse a substantial dataset of over 48,000 structure fire incidents in Oregon, which occurred between January 2012 and August 2023. A key finding of this work is the identification of critical predictors for injury severity. These include victim age, the presence and operational status of smoke or fire detectors, and the response times of fire services. The study also highlights geographic disparities in fire risks and resource requirements across Oregon. This information offers actionable insights for improving firefighting strategies, optimizing resource allocation, and guiding targeted safety education initiatives. Consequently, these findings are particularly relevant for developing spatially aware risk mitigation approaches [3].

Finally, other scholarly work has explored the optimisation of water-based fire suppression systems. Within this research area, a primary objective is often to determine the most effective sensor combinations for the timely activation and deactivation of these systems. Achieving this timeliness is paramount to minimise water usage while ensuring effective fire containment and suppression. Such studies frequently emphasize the benefits of systems incorporating real-time feedback from the fire scene, which allows for more dynamic and efficient resource allocation. These collective findings support the development of advanced firefighting technologies aimed at optimising water consumption and enhancing overall suppression effectiveness through intelligent monitoring and control [4].

II. Data Preprocessing

This project involved a comprehensive data preprocessing pipeline to prepare the dataset for subsequent analysis and model training. Key tasks within this pipeline included ensuring data quality, handling inconsistencies, and transforming raw data into a format suitable for machine learning algorithms. The ultimate aim of these steps was to enhance model performance and interpretability. The following sections detail the specific methodologies applied during this preprocessing phase, covering data quality assessment, missing value treatment, feature engineering and elimination, feature importance analysis, and various data transformation techniques.

A. Data Quality Assessment

The initial data preparation phase focused on a thorough quality assessment. This began with examining the data type of each attribute to ensure it aligned with its expected nature (e.g., numerical, categorical, temporal). Subsequently, descriptive statistics were computed for numerical features to understand their central tendencies, dispersion, and overall distributions. Visual inspection of data samples, such as examining the head of the dataframe, provided an initial overview of the dataset's structure and content. This step was crucial for identifying obvious issues like inconsistent formatting or erroneous entries that could compromise subsequent analyses. Lastly, columns were renamed to improve clarity and maintain consistency in feature nomenclature.

B. Handling Missing Values

Addressing missing data was a critical step in preparing a robust dataset, as several attributes contained missing entries. For certain features, particularly those related to building structure, missing values were imputed with the specific category "YAPI_DEGIL" (meaning "NOT_A_BUILDING"). This imputation was based on the reasoning that if the building type was unspecified, the incident likely did not involve a building. Following these specific imputations, a different strategy was employed for all other features: any rows still containing missing values were removed from the dataset. While this approach (listwise deletion) potentially reduced the dataset's size, it ensured that the data used for model training was complete, thereby preventing complications often introduced by missing values in analytical models.

Separately, for features concerning casualty counts (e.g., male, female, firefighter fatalities/injuries, and various animal fatalities), missing values were initially filled with zero. These zero-filled entries were then aggregated into total counts for each category. This treatment of casualty data was based on the assumption that a missing value in these specific columns signified an absence of casualties of that type.

C. Feature Elimination and Feature Generation

Feature engineering played a significant role in refining the dataset for analysis. This process began with the elimination of several original features deemed irrelevant or redundant for the intended analysis. These included an identifier column, detailed date breakdowns, and granular casualty statistics (such as separate counts for male, female, and firefighter casualties, as well as various types of animal fatalities).

In place of the detailed casualty columns, new aggregate features were generated. Specifically, total human fatalities, total injuries, and total animal fatalities were calculated by summing their respective constituent columns. This consolidation streamlined the feature space while preserving essential information about incident outcomes.

Additionally, the feature representing fire incident type underwent a mapping process. Specific, granular categories within this feature were grouped into broader, more generalized classifications. This approach reduced the dimensionality of this categorical feature and aimed to improve model generalizability. For instance, various types of vegetation fires, such as "OT" (grass) or "AĞAÇ" (tree), were mapped to the general category "Bitki Örtüsü - Tarımsal Alan Yangınları" (Vegetation - Agricultural Area Fires).

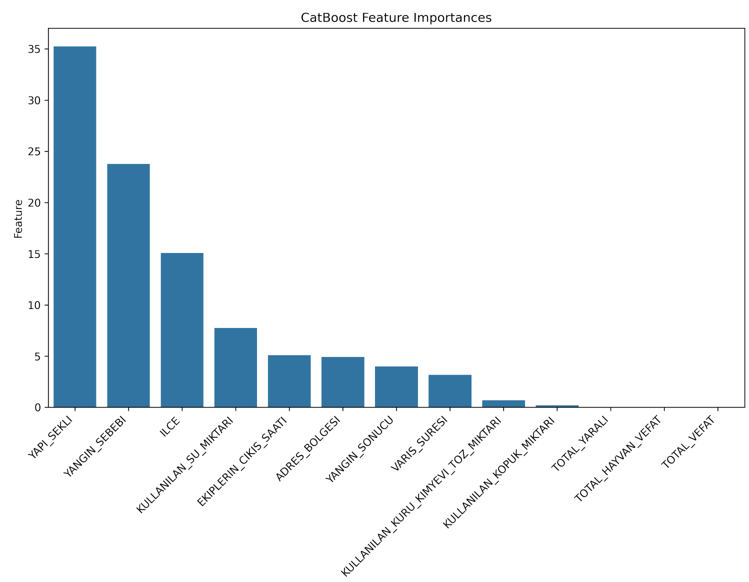

Fig. 1. Feature importance calculated via CatBoost

D. Feature Importance or Redundancy using a Feature Selection Algorithm

To identify the most influential features for predicting the target variable (fire type), a feature importance analysis was performed using a gradient boosting classifier. After this model was trained on the preprocessed dataset, its intrinsic feature importance scores were extracted and visualized. The results highlighted that features such as building structural type, fire cause, incident district, water usage amount, and team departure time ranked among the most significant predictors.

Such analysis is crucial for understanding the data's underlying dynamics, potentially guiding subsequent feature engineering efforts, and for selecting a more parsimonious feature set for final model development. This selection process, by eliminating redundant or irrelevant attributes, can contribute to simpler, more interpretable, and often more robust models.

E. Data Preprocessing

The final stage of preprocessing involved transforming features into a format suitable for machine learning algorithms. Numerical features, including the arrival time of emergency services, the quantities of suppressants used (foam, water, dry chemical powder), and the newly generated total casualty counts, underwent standardization. This process scales data to have a zero mean and unit variance, which is beneficial for many algorithms sensitive to feature magnitudes. Categorical features, including the cause of the fire, building structural type, district, address region, and the outcome of the fire, were transformed using a one-hot encoding scheme. This method converts each category into a new binary feature, thereby preventing unintended ordinal interpretations of nominal data.

One specific numerical feature, related to the teams' departure time, received distinct treatment. It was initially converted into minutes. Subsequently, it underwent a custom transformation (values were divided by 24 and then multiplied by 60), reportedly to represent it within a specific range or to align with a cyclical interpretation of time. Importantly, unlike other numerical features, this custom-transformed departure time feature was then passed directly to model training without undergoing the above standardization scaling.

This comprehensive preprocessing pipeline ensured that the data was clean, consistently formatted, and appropriately transformed for the subsequent modeling phase.

III. Statistical Tests

A. Fire Response Times

Null Hypothesis (H_0): The mean response times are the same across all fire types.

$$H_0 : \mu_1 = \mu_2 = \ldots = \mu_k \quad (1)$$

Alternative Hypothesis (H_A): At least one fire type has a different mean response time compared to the others.

$$H_A : \text{At least one } \mu_i \text{ differs, for } i \in \{1, 2, \ldots, k\} \quad (2)$$

The primary objective of this statistical investigation was to ascertain whether there are statistically significant variations in the average emergency response times (`VARIS_SURESI`) when considering different categories of fire incidents (`YANGIN_TURU`). The initial phase of the analysis involved assessing the underlying assumptions for parametric testing. The Shapiro–Wilk test, applied independently to each fire type group, indicated that **the data for `VARIS_SURESI` did not conform to a normal distribution for any of the examined groups (all $p < .05$).**

Further diagnostic testing involved evaluating the homogeneity of variances across the groups using Levene's test. The outcome of Levene's test was statistically significant ($W(5, N_{\text{total}} - 6) = 3.987$, $p = .001292$), leading to the rejection of the null hypothesis of equal variances. This result signifies that **the variability in response times significantly differs among the various fire categories.** The presence of both non-normality and heteroscedasticity necessitated the use of an alternative to the standard ANOVA.

Consequently, Welch's ANOVA, a robust test that does not require the assumption of equal variances, was employed to compare the mean response times. The Welch's ANOVA test yielded a statistically significant result ($F(5, 550.790612) = 60.676$, $p < .0001$). This indicates that there is a significant overall difference in the mean response times associated with at least two of the fire type categories. The partial eta-squared ($\eta_p^2 = .0041$) indicates that **the fire type accounts for a small but statistically significant proportion of the variance in response times.**

Given the significant result from Welch's ANOVA, a post-hoc analysis was conducted to identify specific pairwise differences between the group means. Since the assumption of homogeneity of variances was violated, the Games–Howell test was selected as the appropriate post-hoc procedure. This test revealed several statistically significant differences in mean response times between specific pairs of fire types. For example, the mean response time for *Bitki Örtüsü - Tarımsal Alan Yangınları* (mean = 6.97) was found to be significantly longer than that for *Altyapı - Ekipman Yangınları* (mean = 5.18, $p < .0001$) and *Araç Yangınları* (mean = 5.49, $p < .0001$). Similarly, *Yapı - Mesken Yangınları* (mean = 4.98) had significantly shorter response times compared to *Araç Yangınları* (mean = 5.49, $p = .003$) and *Bitki Örtüsü - Tarımsal Alan Yangınları* (mean = 6.97, $p < .0001$). Conversely, *Bitki Örtüsü - Tarımsal Alan Yangınları* also exhibited significantly longer response times than *Diğer - Belirsiz Yangınlar* (mean = 5.23, $p = .0045$). These specific comparisons underscore the practical implications of the overall significant ANOVA result, demonstrating that the nature of the fire incident is a crucial determinant of the time taken for emergency services to arrive. In summary, the comprehensive statistical analysis robustly supports the conclusion that **average emergency response times vary significantly across different types of fire incidents**.

B. Water Usage

Null Hypothesis (H_0): The mean water usage is the same across all fire types.

$$H_0 : \nu_1 = \nu_2 = \ldots = \nu_k \quad (3)$$

Alternative Hypothesis (H_A): At least one fire type has a different mean water usage compared to the others.

$$H_A : \text{At least one } \nu_i \text{ differs, for } i \in \{1, 2, \ldots, k\} \quad (4)$$

After examining response times, the investigation then analyzed whether significant differences also exist in the average quantity of water utilized (KULLANILAN_SU_MIKTARI) across the various fire incident classifications (YANGIN_TURU). As with the prior variable, initial diagnostic checks were performed. The Shapiro–Wilk test was applied to KULLANILAN_SU_MIKTARI for each fire type. The results indicated that **the data for water usage also departed from a normal distribution within all categories** ($p < .05$)**.**

Subsequently, the assumption of homogeneity of variances for water usage was evaluated using Levene's test. This test returned a statistically significant result ($W(5, N_{\text{total}} - 6) = 11.162$, $p < .0001$), signifying that **the variability in water consumption is unequal among the different fire types.** The findings concerning the non-normality and heteroscedasticity of water usage are consistent with the conditions observed for response times.

Therefore, Welch's ANOVA was employed to compare the mean water usage. The analysis yielded a highly statistically significant outcome ($F(5, 543.095) = 24.071$, $p < .0001$), demonstrating a significant overall difference in mean water consumption based on the fire category. The partial eta-squared value ($\eta_p^2 = .004128$) indicates the **proportion of variance in water usage attributable to the type of fire.**

To further elucidate the specific inter-group differences in water usage, a Games–Howell post-hoc test was conducted. This detailed pairwise comparison revealed several notable distinctions. For example, *Yapı - Mesken Yangınları* (mean = 5.89 units) required significantly more water on average than *Altyapı - Ekipman Yangınları* (mean = 1.02 units, $p < .0001$), *Araç Yangınları* (mean = 1.33 units, $p < .0001$), and *Atık - Hurda - Depolanmış Malzeme Yangınları* (mean = 3.02 units, $p = .004$). Moreover, *Bitki Örtüsü - Tarımsal Alan Yangınları* (mean = 4.24 units) also showed a significantly greater mean water usage compared to both *Altyapı - Ekipman Yangınları* ($p < .0001$) and *Araç Yangınları* ($p < .0001$). These findings clearly establish that, similar to response times, the specific category of a fire incident is a significant factor influencing the volume of water consumed during firefighting efforts. This second set of analyses focusing on water usage further underscores **the distinct resource demands associated with different fire types.**

IV. Methods and Results

A. Hyperparameter Tuning

The CatBoost algorithm was selected for model development, primarily due to its proficient handling of categorical data and its inherent mechanisms, such as *ordered boosting* and *symmetric tree growth*, which mitigate overfitting and often yield robust performance. Hyperparameter optimization was conducted using RandomizedSearchCV coupled with a 3-fold cross-validation strategy to ensure reliable performance estimation and prevent overfitting to a specific data partition. The $\mathbf{F1_{macro}}$ score served as the guiding metric for this optimization process, chosen for its balanced assessment of precision and recall across all classes. A particularly important consideration in multi-class scenarios or in the presence of uneven class distributions.

The initial test dataset was divided into two distinct sets: a final, held-out test set for performance evaluation and a validation set, which was used specifically for the hyperparameter tuning phase.

The tuning process systematically explored a predefined search space for key CatBoost parameters. This included adjusting the number of iterations (trees), the learning_rate, tree depth, the l2_leaf_reg regularization strength, border_count for numerical feature splits, bagging_temperature, and random_strength for split scoring. The 3-fold cross-validation inherently managed the validation process, where different subsets of the training data were iteratively used for validation, ensuring that the chosen hyperparameters generalized well across different data segments. The parameter set achieving the highest average $\mathbf{F1_{macro}}$ score during this cross-validated search was adopted for the final model configuration.

B. Modelling

TABLE I
Summary of Classification Metrics for Baseline and Main Model

Metric	**Baseline**	**CatBoost**
Accuracy	0.26	0.81
Macro Avg. Precision	0.18	0.75
Macro Avg. Recall	0.19	0.74
Macro Avg. F1-score	0.1844	0.7328
Weighted Avg. Precision	0.26	0.81
Weighted Avg. Recall	0.26	0.81
Weighted Avg. F1-score	0.26	0.81
MCC	-0.0226	0.7350
AUC Scores (Per Class)		
Altyapı - Ekipman Yangınları	0.4977	0.9591
Araç Yangınları	0.4855	0.9778
Atık - Hurda - Depolanmış Malzeme Yangınları	0.4939	0.8916
Bitki Örtüsü - Tarımsal Alan Yangınları	0.4735	0.9115
Diğer - Belirsiz Yangınlar	0.5981	0.8178
Yapı - Mesken Yangınları	0.5007	0.9986

The baseline DummyClassifier, configured with a *stratified* strategy, exhibited performance characteristic of random guessing, as evidenced by its low metric scores. It achieved an overall accuracy of 0.26, a macro average F1-score of 0.1844, and a weighted average F1-score of 0.26. Critically, its Matthews Correlation Coefficient (MCC) was -0.0226, indicating no meaningful correlation between its predictions and the actual classes. The ROC curves for the baseline model, depicted in the provided figure, further underscore this poor performance, with Area Under the Curve (AUC) values for most classes hovering around 0.50: *Altyapı - Ekipman Yangınları* (AUC = 0.50), *Araç Yangınları* (AUC = 0.49), *Atık - Hurda - Depolanmış Malzeme Yangınları* (AUC = 0.49), *Bitki Örtüsü - Tarımsal Alan Yangınları* (AUC = 0.47), and *Yapı - Mesken Yangınları* (AUC = 0.50). The *Diğer - Belirsiz Yangınlar* class showed a slightly higher AUC of 0.60, though still indicative of weak discriminatory power. These results confirm that the baseline model lacks any significant predictive capability.

In contrast, the `CatBoostClassifier` demonstrated substantially superior performance across all evaluated metrics and classes. The CatBoost model achieved an impressive overall accuracy of 0.81, a macro average F1-score of 0.7328, and a weighted average F1-score of 0.81. The MCC for the CatBoost model was 0.7350, signifying a strong positive correlation between its predictions and the ground truth. The ROC curve analysis for the CatBoost model vividly illustrates its enhanced discriminative ability. The AUC values were consistently high across all fire categories: *Altyapı - Ekipman Yangınları* (AUC = 0.96), *Araç Yangınları* (AUC = 0.98), *Atık - Hurda - Depolanmış Malzeme Yangınları* (AUC = 0.89), *Bitki Örtüsü - Tarımsal Alan Yangınları* (AUC = 0.91), *Diğer - Belirsiz Yangınlar* (AUC = 0.82), and remarkably, *Yapı - Mesken Yangınları* achieved a perfect AUC of 1.00.

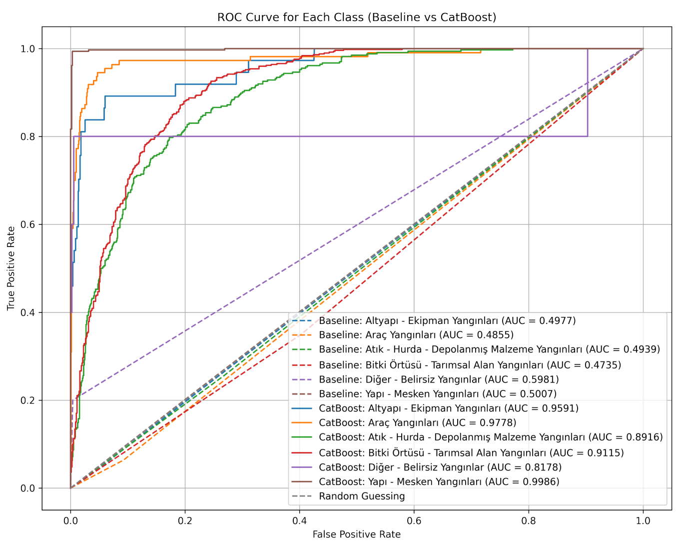

Fig. 2. ROC Curve

The comparison clearly reveals the CatBoost model's profound advantage. It improved accuracy by 211% relative to the baseline. The macro average F1-score saw an increase from 0.1844 to 0.7328, and the MCC surged from a negligible -0.0226 to a robust 0.7350. This substantial improvement in all key performance indicators firmly establishes the efficacy of the CatBoost algorithm for this classification task, providing a reliable and accurate model for predicting different types of fire incidents.

The ROC corresponding to the baseline model are observed to align closely with the diagonal axis of the ROC space, a characteristic indicative of limited discriminative power. In stark contrast, the CatBoost model demonstrates a significant improvement in classification efficacy; its ROC curves for all classes exhibit a pronounced displacement towards the optimal upper-left region. This displacement signifies substantially better true positive to false positive rate trade-offs across the operational spectrum. Consequently, these visual data underscore the enhanced capability of the CatBoost classifier to distinguish between the various fire categories relative to the baseline model.

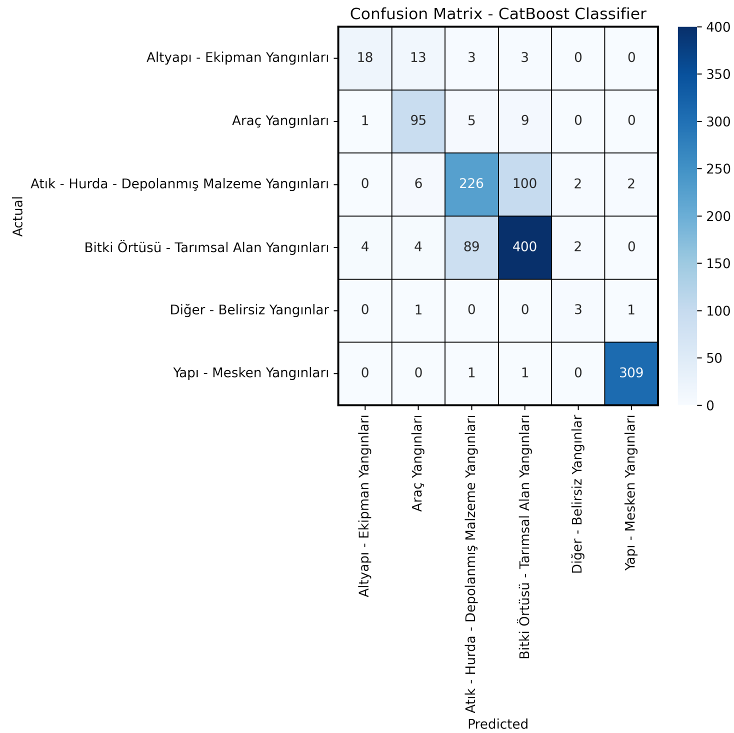

Fig. 3. Confusion Matrix of CatBoost

The `CatBoost` classifier's confusion matrix demonstrates generally high predictive accuracy across the six fire categories. Exceptional accuracy was achieved for *Yapı - Mesken Yangınları* (309 of 311 instances correctly identified), with *Araç Yangınları* (95/110) and *Bitki Örtüsü - Tarımsal Alan Yangınları* (400/499) also showing robust classification. However, some misclassifications were noted: *Altyapı - Ekipman Yangınları* had 18 of 37 instances correctly identified, with 13 misclassified as *Araç Yangınları*. Significant mutual confusion was observed between *Atık - Hurda - Depolanmış Malzeme Yangınları* (226/336 correct) and *Bitki Örtüsü - Tarımsal Alan Yangınları* (400/499 correct), with 100 instances of the former predicted as the latter, and 89 instances vice-versa. The *Diğer - Belirsiz Yangınlar* category, with limited support (5 instances), had 3 correctly classified. While the classifier is broadly effective, these specific inter-class confusions, particularly between *Atık - Hurda - Depolanmış Malzeme Yangınları* and *Bitki Örtüsü - Tarımsal Alan Yangınları*, indicate areas for targeted model refinement.

C. Interpretability

To assess the influence of each feature on the model's decision-making process, the built-in feature importance scores from the `CatBoost` algorithm were utilized. As demonstrated in the provided feature importance plot (see **Fig. 1.**), `YAPI_SEKLI` was identified as the most influential feature, followed by `YANGIN_SEBEBI` and `ILCE`. Other features demonstrating notable importance included `KULLANILAN_SU_MIKTARI` (Amount of Water Used), `EKIPLERIN_CIKIS_SAATI`, and `ADRES_BOLGESI`. These findings are largely consistent with expectations from fire incident analysis literature, where factors such as the structural characteristics of the involved property, the ignition source or cause, and the geographical location (which can correlate with response times and building densities) are commonly recognized as significant determinants of fire outcomes and severity. The prominence of these features indicates that the model has learned relevant patterns from the data.

V. Discussion

This study successfully analyzed key fire response metrics using the 'Izmir 2023 Fire Response Statistics' dataset, offering valuable insights for enhancing fire management strategies. The findings demonstrate statistically significant variations in average response times and water usage across different fire types. These insights are crucial for societal and environmental benefits, particularly in fire prevention, risk assessment, and resource planning. For instance, understanding that *Bitki Örtüsü - Tarımsal Alan Yangınları* have longer average response times and relatively high water usage can guide targeted prevention programs and ensure adequate resource availability for such incidents. This data-driven approach to resource allocation aligns with literature emphasizing tailored predictive models and optimized water usage for effective fire risk management and suppression. The identification of critical predictors like building type and fire cause further aids in developing spatially aware risk mitigation approaches, similar to findings in other studies focusing on diverse data integration for comprehensive risk assessment.

The initial research questions were comprehensively addressed. Firstly, statistical analyses (Welch's ANOVA and Games-Howell test) confirmed significant differences in mean response times across various fire types. Secondly, similar statistical methods revealed significant variability in water usage among different fire categories. Thirdly, the feasibility of predicting fire incident types was established through the development of a CatBoost classifier, which achieved high accuracy (0.81) and a MCC of 0.7350, significantly outperforming the baseline model and demonstrating strong predictive capability comparable to findings in other machine learning-based fire prediction research. Advantages of this study include a thorough data preprocessing pipeline, the use of appropriate statistical tests for non-parametric data, and the successful application of a robust classification model with feature importance analysis. However, limitations include the study's geographical specificity to Izmir, potentially limiting direct generalizability without further validation. Additionally, some inter-class confusion was observed in the model, particularly between *Atık Hurda Depolanmış Malzeme Yangınları* and *Bitki Örtüsü - Tarımsal Alan Yangınları*, and the *Diğer - Belirsiz Yangınlar* category had limited instances.

Future work will focus on refining the predictive model to mitigate observed misclassifications, possibly by incorporating additional features or exploring alternative modeling techniques. Expanding the analysis to include data from other regions would enhance the generalizability of the findings. Furthermore, integrating dynamic data sources, such as meteorological data or socio-economic indicators as suggested by studies [1], could improve predictive accuracy. Investigating the influence of local urban dynamics and potentially applying time series models for certain fire types, as explored in studies [2], could also provide deeper insights for proactive fire management and resource optimization.

VI. Data And Code Availability

This research utilized the 'Izmir 2023 Fire Response Statistics' dataset. Statistical analyses employed Welch's ANOVA and the Games-Howell post-hoc test, while predictive modeling involved a CatBoost classifier benchmarked against a DummyClassifier. For reproducibility, the source code, experimental notebooks, and processed data are available at: [github.com/erdikilic/DI501_Term_Project]

Disclaimer

This work has benefited from the use of Large Language Models (LLMs), including **Gemini**, **DeepSeek-R1**, and **DeepL**, which were employed to assist in improving the clarity of language, the quality of written expression, and the accuracy of LaTeX formatting. These tools were used exclusively for linguistic and presentational enhancement and did not influence the content or originality of the work.

References

[1] C.-Y. Ku and C.-Y. Liu, "Predictive modeling of fire incidence using deep neural networks," Fire, vol. 7, no. 4, p. 136, Apr. 2024. doi:10.3390/fire7040136.

[2] Y. Yuan and A. G. Wylie, "Comparing machine learning and time series approaches in predictive modeling of urban fire incidents: A case study of austin, Texas," ISPRS International Journal of Geo-Information, vol. 13, no. 5, p. 149, Apr. 2024. doi:10.3390/ijgi13050149 .

[3] A. Schmidt, E. Gemmil, and R. Hoskins, Machine learning based risk analysis and predictive modeling of structure fire related casualties, 2024. doi:10.2139/ssrn.4757205.

[4] G. V. Kuznetsov, A. O. Zhdanova, R. S. Volkov, and P. A. Strizhak, "Optimizing firefighting agent consumption and fire suppression time in buildings by forming a fire feedback loop," Process Safety and Environmental Protection, vol. 165, pp. 754–775, Sep. 2022. doi:10.1016/j.psep.2022.07.061.