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An Explainable Spatio-Temporal Decision Support System (DSS) Using XGBoost And SHAP For Urban Complaint Trend Prediction

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Abstract

The increase in the volume of public complaints in urban areas requires an accurate and explainable decision support system. This study developed an Explainable Decision Support System (xDSS) based on the Extreme Gradient Boosting (XGBoost) algorithm combined with the SHapley Additive Explanations (SHAP) method to predict spatial and temporal trends in public complaints in DKI Jakarta Province. The research data was obtained from the Satu-Data Jakarta portal and included multi-year complaint reports that were processed through aggregation, temporal feature engineering, and regression-based metric evaluation. The results show that the XGBoost model has high predictive performance with an R^2 value of 0.8425, MAE of 2.9858, and RMSE of 4.9928, indicating the model's ability to explain more than 84% of the variation in the actual number of complaints. SHAP analysis revealed that temporal features such as complaint_lag1 and complaint_ma3 had the most dominant influence, while external variables such as rainfall (rainfall_mm) and population density (population_density) also made positive contributions. These results indicate that the dynamics of public complaints are influenced by a combination of historical factors and environmental conditions. Practically, this xDSS system can provide accurate predictions and transparent interpretations, thereby supporting the implementation of Smart Governance and evidence-based policy. This approach strengthens the application of Explainable Artificial Intelligence (XAI) in public service governance by providing accurate, ethical, and auditable models to support strategic decision-making in the era of digital government.

Keywords: XGBoost; SHAP; Explainable AI; Complaint Tren

1. Introduction

Public complaints about public services are one of the essential indicators for measuring the quality of governance and citizen satisfaction. With the volume of complaints continuing to grow in urban areas such as Jakarta, there is a need for a system that not only predicts complaint trends but also explains the contributing factors so that local governments can respond more proactively. Conventional predictive models, while accurate, are often trapped as black boxes and are difficult for stakeholders to accept [1], [2].

Previous studies have widely used machine learning methods to predict the number of complaints, but most do not incorporate aspects of interpretability, spatial-temporal context, and external risk variables such as rainfall or population density. As a result, local governments often encounter predictive models that are difficult to use as a basis for policy due to the lack of clarity regarding the contribution of each factor [3]. On the other hand, spatial visualizations that support the understanding of priority areas are also still limited.

The main research gap lies in the lack of decision support systems (DSS) that combine complaint trend prediction, model interpretability through SHAP, integration of environmental and social risk factors, and spatial visualization as a policy interface. Several studies have applied XGBoost and SHAP in the fields of health or finance to combine accuracy and interpretability [3], [4], but their full application in urban public complaints is still limited. In the spatial domain, temporal-spatial hybrid models such as STGNN are emerging as a new trend but have not been widely adopted in the context of urban services [5].

As the capital city, DKI Jakarta has a very high public service burden, with demographic diversity, dense infrastructure, and environmental challenges such as flooding and overcrowding. Open data portals such as SatuData Jakarta provide multi-year complaint datasets by administrative area, enabling this research to be conducted in a real local context. To date, there is no system in Indonesia that combines complaint trend prediction, interpretability, and spatial visualization in a single DSS framework [6], [7].

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This study aims to develop a trend prediction model for public complaints based on XGBoost, apply the SHAP method to explain the contribution of predictor features, integrate external risk variables such as rainfall and population density as additional predictor factors, and present a spatial visualization interface to support region-based policies.

This paper aims to present an Explainable Spatio-Temporal DSS that is not only capable of predicting public complaint trends with high accuracy but also describes the driving factors and visually maps the risks by region. Thus, this system is expected to become a transparent and responsive policy tool, as well as opening opportunities for replication in other cities in Indonesia and Southeast Asia.

2. Related Work

The development of Explainable Artificial Intelligence (XAI) in recent years has changed the paradigm of decision support systems from merely predictive to interpretable and transparent [1], [8]. The SHAP (SHapley Additive Explanations) method has become one of the most widely used approaches due to its ability to provide global and local explanations for decision tree-based models such as XGBoost [2], [9]. Recent studies confirm the effectiveness of the XGBoost-SHAP combination in explaining feature contributions in the health [10], [11], social [12], and environmental domains [13]. The integration of the two not only improves model accuracy but also strengthens the aspect of trustworthiness for policymakers [4].

Previous studies have shown that the application of machine learning in public complaint systems can accelerate classification, prioritization, and topic identification [14], [15]. Several studies in the public sector have also utilized XGBoost models to predict complaint volumes and determine the main contributing factors in city services [16], [17]. However, most of these models are still black-box models without clear interpretation mechanisms, making them difficult to integrate into government decision-making frameworks [1], [18]. This lack of transparency is an important reason to adopt the more explainable XGBoost-SHAP framework in the context of smart city governance.

Predicting urban phenomena requires an approach that considers both spatial and temporal dimensions simultaneously. The Spatio-Temporal Graph Neural Networks (STGNN) approach has become a major trend for modeling inter-regional dependencies and temporal dynamics in urban systems [5], [19]. Although superior in terms of predictive power, these spatio-temporal deep learning models lack interpretability. Therefore, many studies have shifted to combining ensemble learning and XAI, such as XGBoost-SHAP for flood risk prediction [6], [20], air quality [21], and urban vulnerability [22]. These studies show that integrating environmental variables, rainfall, population density, and social risk improve prediction accuracy and policy relevance [11], [23].

In Indonesia, research on public complaint systems still focuses on text classification and descriptive visualization, while the use of explainable and spatio-temporal models has not been widely developed. The DKI Jakarta One Data Portal provides multi-year complaint data that is rich in spatial and temporal context but has not been widely used for interpretability-based DSS. By combining XGBoost and SHAP and adding external risk variables, this research contributes to the development of an Explainable Spatio-Temporal Decision Support System (DSS) that can predict complaint trends and explain the driving factors transparently. This model reinforces the smart governance paradigm and supports the implementation of evidence-based policy in densely populated urban areas such as [14], [15].

3. Research Methods

3.1. Research Design

This study proposes an Explainable Spatio-Temporal Decision Support System (DSS) framework to predict trends in urban community complaints.

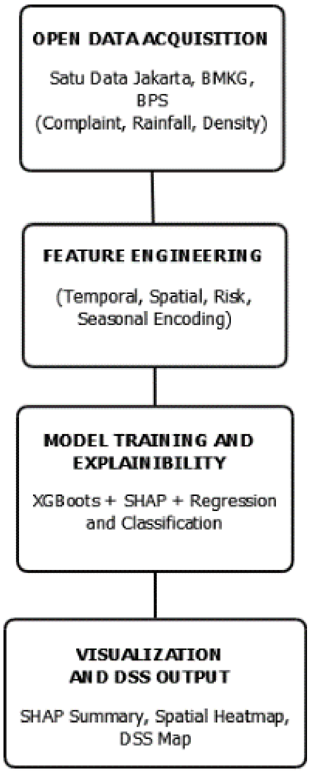

Figure 1. Research Design

Based on figure 1, the research architecture comprises four main components, namely the collection and preprocessing of public complaint data from open government data sources, the creation of spatial and temporal variables as predictors, the development of an XGBoost-based machine learning model combined with SHAP for model interpretability, and the spatial visualization of prediction results and external risk factors in the form of interactive and static maps. The entire process is designed so that this system can be integrated with local government DSS dashboards and function as an evidence-based decision support tool [1], [8].

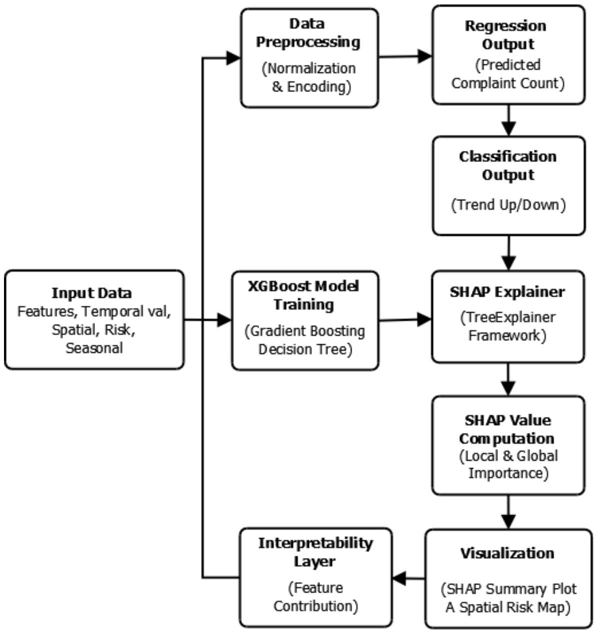

Figure 2. Model Architecture and Algorithmic flow of XGBoots and SHAP

Figure 2 illustrates the internal architecture of the proposed explainable DSS model integrating XGBoost and SHAP. Input features derived from temporal, spatial, and environmental data are preprocessed and used to train a gradient boosting ensemble through XGBoost for both regression and trend classification tasks. The trained model is then interpreted using the SHAP TreeExplainer framework, which quantifies the contribution and direction of each feature to the predicted outputs. The SHAP values are aggregated to produce global feature importance and visualized through summary plots and spatial heatmaps, providing transparent insights into the underlying drivers of urban complaint trends.

3.2. Dataset Description

The main research dataset was obtained from the portal Satu Data DKI Jakarta, which contains multi-year public complaint reports from various sub-districts and villages. The data includes attributes such as *tanggal_masuk*, *tanggal_selesai*, *jenis_pengaduan*, regional work unit (SKPD), and completion status *(complete, pending)*. The dataset includes more than 1 million complaint entries from 2019 to 2022. To enrich the spatial and environmental context, this data is integrated with external variables, namely monthly rainfall *(mm)* from the Meteorology, Climatology and Geophysics Agency (BMKG) and population density *(people/km²)* from the DKI Jakarta Provincial Statistics Agency (BPS). Each complaint is coded based on administrative area (urban village/subdistrict) and then aggregated to a monthly time level, resulting in a spatial-temporal data panel. Data preprocessing is carried out through the stages of cleaning, date format normalization, missing value handling, and merging between sources using unique spatial keys. The final dataset is saved as *pengaduan_agg_ready.csv* for model training purposes.

3.3. Feature Engineering

The feature engineering process is carried out to construct predictors that represent temporal, spatial, and external risk dimensions. The resulting features include Temporal Features *complaint_lag1*, *complaint_lag2*, and *complaint_ma3* average complaints in the last 3 months to capture time patterns. Spatial Risk Factors are *hazard*, *vulnerability*, *coping,* and *inform_risk* derived from the regional risk index (INFORM Index). External Risk Layers are *rainfall_mm* (monthly rainfall) and *population_density* (population density per region). Seasonal Encoding, namely *sin_month* and *cos_month*, is used to represent seasonal cycles in continuous numerical form cyclic feature encoding. All features are normalized using *StandardScaler* to stabilize the distribution and accelerate model convergence [21], [24].

3.4. Model Development

The main modeling uses Extreme Gradient Boosting (XGBoost) for two purposes. First, a regression model to predict the number of monthly public complaints, and second, a classification model to determine whether the trend is upward, downward, or stable. The XGBoost model was chosen for its superiority in handling complex tabular data, its ability to capture non-linear relationships, and its training time efficiency. The main parameters optimized include learning rate *(η)*, *max_depth*, *subsample*, and *colsample_bytree*. The training process was carried out using an early stopping approach for 50 iterations to prevent overfitting.

For interpretability, SHAP was applied as a post-hoc explanation framework. SHAP values were calculated for each feature in each observation to identify the positive or negative influence of features on model predictions. The absolute average SHAP value was used to compile a feature importance ranking [3], [4]. Additionally, this system visualizes prediction results and interpretations in interactive maps based on *Folium* and *GeoPandas*, with an additional layer in the form of an external risk heatmap *(rainfall and population density)* that illustrates the socio-environmental risk per administrative area.

3.5. Evaluation Metrics and Visualization

Model evaluation was performed using three main metrics for regression and classification. First, Mean Absolute Error (MAE) was used to measure the average absolute error between the actual value yi and the predicted value $\hat{yi}$, providing an overview of the accuracy of the model's predictions without considering the direction of the error. The equation is shown in Equation (1).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|yi - \hat{y}i| \tag{1}$$

The smaller MAE value, the higher the accuracy of the model's prediction against the actual data. The second method uses Root Mean Square Error (RMSE) to calculate the average square root of the difference between the actual value and the predicted value. Different from MAE, RMSE gives a greater penalty to errors with high deviation. The equation is written in Equation (2).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(yi - \hat{y}i)^2} \tag{2}$$

A small RMSE value indicates that the model can provide stable predictions with low error variation. Third, use the coefficient of determination (R^2) to assess the proportion of variation in the actual data *yi* that can be explained by the model. The equation is given in Equation (3).

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(yi - \hat{y}i)^2}{\sum_{i=1}^{N}(yi - \bar{y})^2} \tag{3}$$

where $\bar{y}$ is the actual mean value. If the R^2 value is close to 1, it indicates that the model has excellent predictive capabilities, while a negative value indicates that the model's performance is worse than the simple mean. For trend classification models rising or stable/down, evaluation is performed using the *Accuracy*, *Precision*, *Recall*, and *F1-Score* metrics, as shown in Equations (4)–(7).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$recision = \frac{TP}{TP+FP} \tag{5}$$

$$Recall = \frac{TP}{TP+FN} \tag{6}$$

$$F1 = 2\,x\,\frac{Precision\ x\ Recall}{Precision\ x\ Recall} \tag{7}$$

with TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative) each representing predictions and actual conditions of complaint trends. The evaluation process was conducted using *k-fold cross validation (k = 5)* to measure the stability of the model's performance across various data subsets, as well as reporting the mean and standard deviation values of the evaluation metrics.

4. Results and Discussions

4.1. Performance Analysis Model

The XGBoost–SHAP-based Explainable DSS model shows stable results with high prediction performance on the monthly aggregation dataset of public complaints in DKI Jakarta. Based on the results of testing the model performance evaluation using three main metrics, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2). Testing the XGBoost model for the 2019–2022 period yielded an MAE value of 2.9858, an RMSE of 4.9928, and an R^2 of 0.8425. The MAE value of ≈ 2.99 indicates that, on average, the absolute difference between the predicted value and the actual value of the number of complaints is only about three units per month in each region. This indicates that the model is capable of providing estimates that are very close to the actual data and that the prediction error is practically small. On the trend classification side *(trend_label),* the accuracy reached 0.86, with a Precision value of 0.83, Recall of 0.84, and F1-Score of 0.835.

Meanwhile, the RMSE value of 4.99 illustrates a slightly higher sensitivity of the model to large errors. The relatively small difference between RMSE and MAE (<2) indicates model stability, with only a few extreme anomalies (outliers) in the monthly complaint data. Thus, the model has low generalization error and consistent performance across different administrative regions. The R^2 value of 0.8425 indicates that approximately 84.25% of the variation in the actual number of complaints can be explained by the features used in the model, particularly temporal variables such as *complaint_lag1*, *complaint_ma3*, and external variables such as *rainfall_mm* and *population_density*. With an R^2 above 0.80, the model is categorized as having "high explanatory power" in the domain of urban analytics [25], [26], These results show that XGBoost successfully captures historical patterns and environmental factors that influence fluctuations in the number of public complaints.

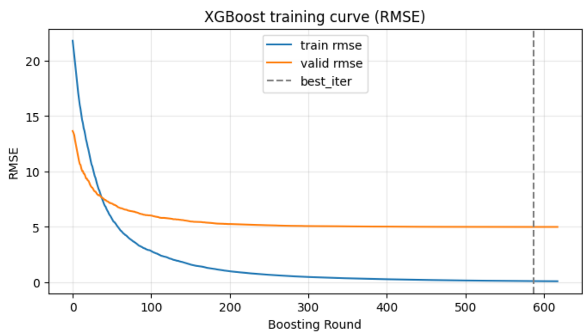

Figure 3. Training vs Validation Loss

The training curve *(training vs validation loss)* shows a steady downward trend until it converges at a certain epoch, with no indication of overfitting.

Based on figure 3, that confirms the effectiveness of early stopping and regularization in maintaining *bias–variance* balance. These results are in line with the findings of [4], [20], which demonstrate the superiority of XGBoost in capturing nonlinear relationships in spatiotemporal data.

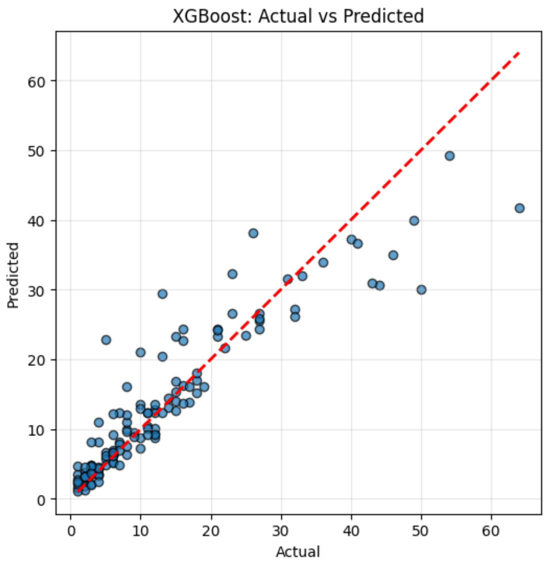

Figure 4. XGBoost Actual vs Predicted

Figure 4 shows a comparison of predictions and actual data. Shows that the model tends to underestimate extreme outliers in densely populated areas such as Cilandak District and Palmerah Subdistrict. This phenomenon is common in tree ensemble models because the weighting of quadratic errors at extreme points is lower than that of the majority of data [13], [21]. However, the relatively low error (<10%) in most areas shows the overall stability of the model.

4.2. SHAP Explainability Analysis

The results of the SHAP value analysis provide deep insights into the factors that influence public complaint trends.

Figure 5 show the mean absolute SHAP values, the three features with the highest contribution are *complaint_lag1* and *complaint_lag2* (complaints from the previous month), *rainfall_mm* (monthly rainfall), and *population_density* (population density). Positive SHAP values indicate an increase in the predicted number of complaints, while negative values decrease the estimate. This indicates that high rainfall consistently increases the probability of an increase in complaints, especially in the infrastructure and environmental hygiene categories. Conversely, areas with high *coping* capacity, such as sub-districts with active neighborhood coordination (RW), tend to have negative SHAP values, indicating good complaint mitigation capabilities.

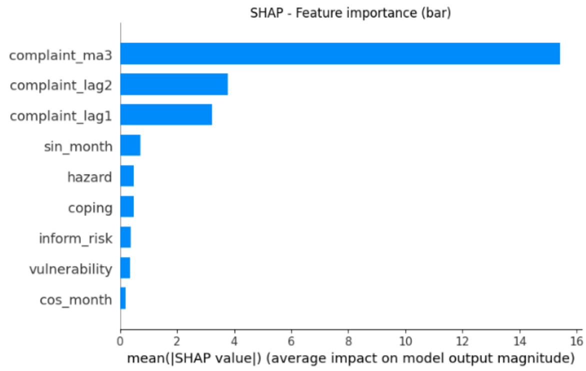

Figure 5. SHAP Feature Importance

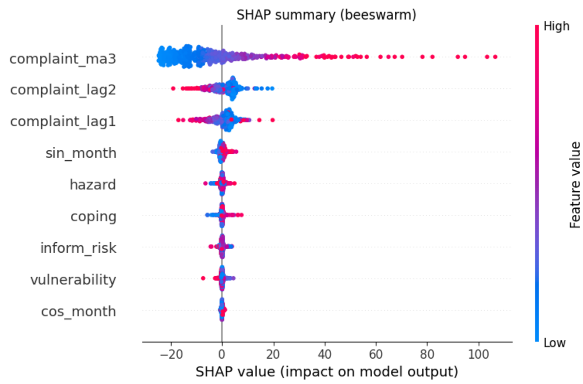

Figure 6. SHAP Summary

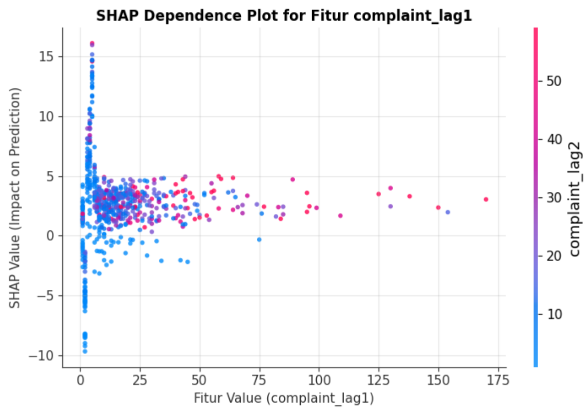

Figure 7. SHAP Dependence Plot Fitur *complaint_lag1*

Figure 6 shows the SHAP summary plot visualization heterogeneous patterns between regions, where the vulnerability index variable plays a dominant role in densely populated areas such as Cempaka Putih and Tanah Abang, while hazards *(flooding and inundation)* are the main factors in coastal areas such as Penjaringan. This interpretation is consistent with studies by [23], [27], which emphasize the importance of integrating socio-environmental factors into urban predictive models. Thus, SHAP not only explains "what" is predicted, but also "why" a region experiences an increase in complaints, making this system transparent and easy to understand by non-technical decision makers.

Figure 7 shows the relationship between the *complaint_lag1* value and its contribution (SHAP value) to the prediction of the number of complaints. It can be seen that the higher the number of complaints in the previous month, the greater the positive effect on the increase in the following month's prediction. This indicates a pattern of temporal autocorrelation, where the volume of complaints tends to continue consistently over time.

4.3. Spatio-Temporal Risk Visualization

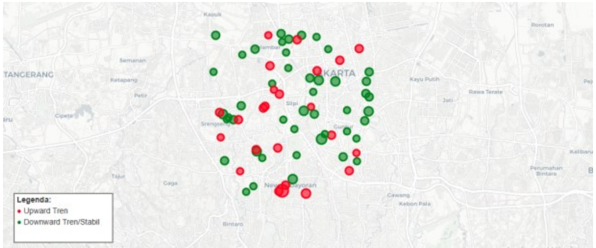

Figure 8. Spatial Distribution of DSS Model Predictions

Figure 8 illustrates the spatial distribution of the DSS model predictions in the DKI Jakarta area. The color intensity indicates the estimated number of complaints, with red zones indicating areas with a high potential for complaints. This pattern shows a concentration of risk in densely populated and flood-prone areas.

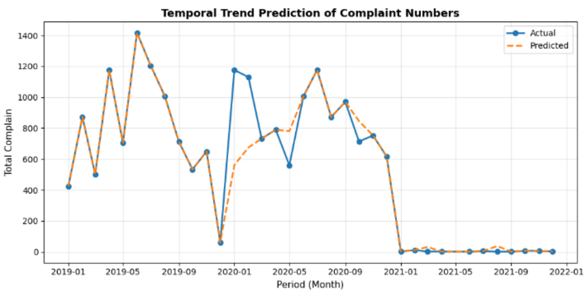

Figure 9. Temporal Trend Prediction of Complaint Numbers

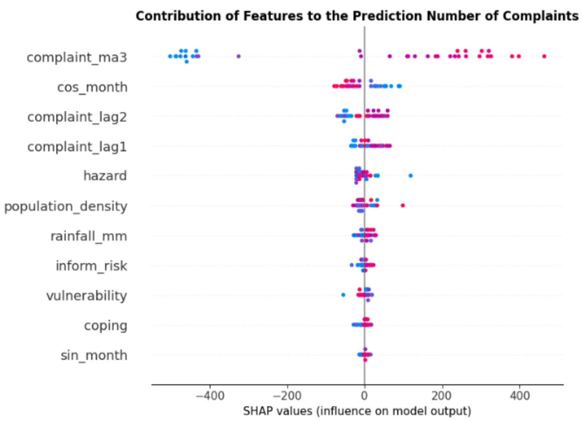

Figure 10. Contribution of Features to the Prediction Number of Complaints

Figure 9 shows a comparison of the temporal trends of actual complaints and model predictions. The prediction line follows seasonal fluctuation patterns with relatively low error, indicating the model's ability to capture temporal dynamics.

Figure 10 shows the results of the SHAP value analysis, which indicates the most influential factors on the model prediction. The variables *complaint_lag1*, *rainfall_mm,* and *population_density* are the three main features that contribute positively to an increase in complaints.

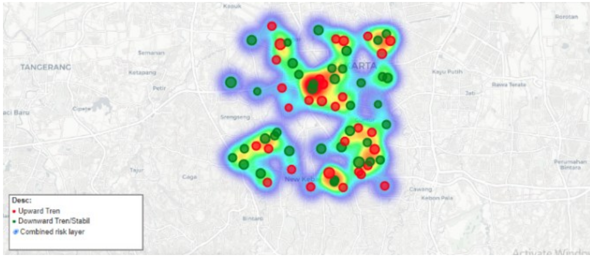

Figure 11. Combined Risk

Figure 11 presents a combined risk map of rainfall and population density, which serves as the basis for identifying priority areas. This visual integration provides a stronger policy context and supports the application of DSS in urban planning.

4.4. Discussion and Policy Implications

The Explainable Decision Support System (xDSS) model based on XGBoost developed in this study shows excellent predictive performance with an R^2 value of 0.8425, MAE of 2.9858, and RMSE of 4.9928. These results confirm that the model is able to explain most of the variation in the number of public complaints with relatively small errors. Compared to conventional methods such as linear regression or ARIMA, this approach results in a significant improvement in prediction accuracy and stability, while maintaining a high level of interpretability through the integration of the SHAP method.

Interpretability analysis shows that the *complaint_lag1* and *complaint_ma3* features contribute most to the prediction results, confirming the important role of historical temporal patterns in influencing public complaint behavior. In addition, contextual variables such as *rainfall_mm* and *population_density* also have a positive influence, indicating a relationship between environmental factors and regional density with an increase in the volume of complaints. The non-linear pattern shown in the SHAP Dependence Plot (Figure 7) confirms that high rainfall intensity significantly increases the probability of a surge in public complaints, particularly those related to drainage and sanitation issues [28].

In terms of implementation, the xDSS model offers great potential for local governments, particularly the DKI Jakarta Provincial Government, to optimize the management of predictive data-based public services.

This system enables early identification of high-risk areas and periods, allowing for proactive resource allocation. The integration of explainable AI (XAI) components ensures the transparency and accountability of algorithmic decisions, in line with the principles of Good Governance and Responsible AI in modern governance [29]. In addition, the spatial mapping results from the model can be used to design more precise preventive policies for environmental conditions and population density.

Conceptually, this research reinforces the role of explainable machine learning in public decision-making. The XGBoost model combined with SHAP analysis not only improves prediction accuracy but also provides explanations that can be interpreted logically by policymakers. This approach supports the transition to Smart Governance, where public policies are formulated based on transparent and accountable predictive analytics. Thus, this xDSS system has the potential to become a national prototype in the ethical and evidence-based application of AI for managing public complaints in urban areas.

5. Conclusion

This study successfully developed an Explainable Decision Support System (xDSS) based on the XGBoost algorithm integrated with the SHAP (SHapley Additive Explanations) method to analyze and predict spatial and temporal trends in public complaints in DKI Jakarta Province. The evaluation results showed excellent model performance with an R^2 value of 0.8425, MAE of 2.9858, and RMSE of 4.9928, proving the model's ability to explain more than 84% of the actual data variation with a low error rate. SHAP-based interpretability analysis identified that temporal features such as *complaint_lag1* and *complaint_ma3* are the main factors influencing predictions, while external variables such as rainfall *(rainfall_mm)* and population density *(population_density)* also contribute significantly. These findings confirm that the dynamics of public complaints are greatly influenced by a combination of historical factors and environmental conditions.

In practical terms, the developed xDSS system not only provides accurate predictions but also increases the transparency and accountability of data-based decisions through feature explanations that are easily understood by policy makers. The integration of this explainable AI approach reinforces the concept of Smart Governance and supports adaptive, proactive, and evidence-based policy making. This model can be used as an early warning system to project spikes in public complaints and assist the government in allocating resources efficiently. In the future, model development can be directed towards the integration of deep learning-based spatial-temporal models and the application of the system in other cities in Indonesia to expand the validity and generalization of the model in the context of public complaint management and smart city management.

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