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Explainable AI for Insurance Premium Prediction Using Multidimensional Urban Risk and Geospatial Analysis

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Abstract-This study presents an integrated deep learning and explainable AI framework for insurance premium prediction using satellite-derived urban risk indicators across 125 localities of Mumbai, India. For each locality, eight high-resolution satellite images were collected and pre-processed, and a transfer learningbased multi-image architecture (ResNet50 with feature aggregation) was employed to generate locality-level urban risk scores. These risk scores were combined with health-related factors (age, BMI, smoking status, chronic conditions, lifestyle attributes) and urbanenvironmental variables (flood exposure, industrial proximity, air quality, population density, property value) to construct a dataset exceeding 100,000 insurance records. Multiple regression models— including Linear Regression, Random Forest, Gradient Boosting, and XG-Boost—were trained and evaluated using MAE, RMSE, and R^2 metrics for premium prediction. To ensure interpretability and regulatory relevance, SHAP and LIME were applied to quantify the contribution of urban and health determinants to pricing outcomes. The proposed framework demonstrates how satellitebased urban intelligence can be systematically integrated into riskadjusted insurance underwriting, offering a scalable and transparent approach for data-driven premium modelling in complex metropolitan settings.

Keywords— Insurance premium prediction, Deep Learning, Ensemble Methods, Machine Learning, Actuarial Science, Generative AI, XG-Boost, Neural Networks, Financial Technology, Personalized Analytics

I. INTRODUCTION

The price of urban insurance is a complex issue based on a large range of risk variables, such as the environmental exposure, effects of climate changes, health status, the quality of infrastructure, or the locality features. The actuarial and rule-based models tend to miss the nonlinear interplay and the spatial heterogeneity of the urban risk environments, leading to low levels of predictive power and black box pricing algorithms. According to the recent implementations of machine learning in geospatial and urban analytics, more sophisticated models could provide better insight into risks, although the majority of the current literature is topic-based or considers researchers one risk type at a time [1,2]. Explainable Artificial Intelligence (XAI) has become an encouraging future of understanding complex predictive models, as the data presented can be meaningful and explains drivers of decisions that are valuable in high stakes applications (insurance underwriting). One of the most common XAI approaches is SHapley Additive exPlanations (SHAP) and other similar methods based on their post-hoc theoretical characteristics along with the possibility to offer global and local interpretability [3]. Nevertheless, the applicability of XAI to insurance premium prediction, in particular, environmental and urban risk is minimally investigated. The previous research on the use of XAI in insurance focuses on the interpretation of the models as opposed to an integrated multidimensional risk and spatial variability analysis. As an example, explainable methods have been used in flood susceptibility and land risks models [4], but limited work exists on detailed premium pricing models that consider geospatial explainability.

Further, geospatial analysis offers important insights at the locality level of analysis by visualizing risks and premium variation across space, which are important to easily and fairly make underwriting decisions. Although there have been improved frameworks of Geo-AI in the assessment of the environment environments and urban risk assessment, there is limited literature on the use of the technology in insurance pricing. A combination of urban environmental gradients, climate change impacts, and flood susceptibilities and the insurance premiums model will provide richer, more practical risk information, especially in fast-urbanizing areas [5].

Contrary to conventional insurance pricing models that rely primarily on demographic and health variables, urban insurance risk in a megacity such as Mumbai is spatially heterogeneous and deeply influenced by locality-specific environmental exposures. Fine-scale differences across neighbourhoods — including flood susceptibility, coastal proximity, built-up density, industrial exposure, green cover depletion, and air quality — significantly shape health and financial vulnerability. However, existing literature rarely integrates these environmental and spatial dimensions into a unified, explainable premium prediction framework at the locality level [6].

This study addresses this gap by proposing an XGBoostbased explainable machine learning system that integrates demographic, health, and geospatial urban risk indicators for insurance premium prediction across fine-grained localities of Mumbai. The framework incorporates satellite-derived urban risk scores and environmental indices, enabling spatially conscious modeling of climate and flood exposure. To ensure interpretability and transparency, SHAP (SHapley Additive Explanations) is employed to quantify the contribution of each feature to premium determination, thereby bridging predictive performance with explainable urban risk intelligence. The proposed approach advances climate-aware and locality-sensitive insurance modeling in emerging megacities [7].

II. LITERATURE SURVEY

Proper forecasting of insurance premiums can be a complicated but important exercise in the solvency of insurance companies as well as in providing clients with reasonable prices. There are a plethora of factors modelled in this process, such as demographics, health indicators, such as BMI, lifestyle choices, and also geographic region. To cope with this complexity, it has been increasingly popular that researchers rely on machine learning (ML) in order to create predictive models. The current literature shows that a lot of attention has been paid to the utilization of different supervised and unsupervised ML models to achieve better predictive accuracy, efficiency, and model interpretability. The work would be a basis to investigate more sophisticated architectures, including Deep Learning, to learn more complex non-linear relationships between policyholder data.

Mahesh et al. (2025) gave a general impression of using predictive analytics to estimate medical insurance cover. Their article is the construction of the predictive models with invoking several methods of machine learning, both regression and an ensemble model distribution, on the basis of a set of demographics and medical history [8].

Sijie et al. (2024) also explored an ensemble machine learning algorithm that is intended to predict health insurance premiums. Instead, they combined their unique method of having an Artificial Neural Network (ANN) to predict its ability using other machine learning frameworks [9].

Bhongade et al. (2024) have dealt with the vital point of model interpretability and developed a predictive model of Explainable AI (XAI) on medical insurance premiums. They employed ensemble learning models, such as Histogram Gradient Boosting, and employed the SHAP (SHapley Additive exPlanations) analysis to explain the decisions of the model [10].

Dash et al. (2024) performed a general comparison of various machine learning regression models in medical insurance premium guess. In their analysis, they tested such models as Linear, Lasso, Ridge and XGBoost to identify what factor (especially age and BMI) wielded the strongest influence on the insurance rates [11].

Pradhan et al. (2024) analyse the impact of land submergence on temperature variations in Asian coastal regions using Random Forest Regression combined with explainable AI techniques (SHAP and LIME). The study advances existing coastal climate literature by moving beyond black-box predictions and explicitly identifying key influencing factors such as land impact, coastal length, and temporal trends. By integrating XAI with machine learning on long-term data (1990–2020), the work improves interpretability and supports transparent, policy-relevant decision-making, addressing a critical gap in explainable climate impact modelling for coastal regions [12].

Linija et al. (2023) investigated how a Linear Support Vector Machine (LSVM) could be applied to a particular task, which is the prediction of medical insurance premiums. They trained and evaluated the LSVM model on eleven different criteria and stated that the predictive accuracy was high with a value of 99 on their data [13].

The article by Jyothsna et al. (2022) was dedicated to the use of the XG-Boost Regressor to predict premiums in health insurance. Their research focused on the investigation of the impact of some essential input parameters, including age, sex, and BMI, on the ultimate predicted premium by the model [14].

Singh and Singh (2022) developed a regression model which is an ensemble-based model with a particular purpose to predict the future health insurance premiums. To justify their methodology, the performance of the proposed model was comparatively done against four other commonly known regression methods in a systematic manner [15].

The authors of the article by Omar et al. (2021) designed a data-driven prediction of the health insurance premiums that involved an unsupervised learning stage. They initially used K-means algorithm in clustering, where they used the Elbow method to determine the best number of clusters to cluster people of various ages after which the premium prediction is performed [16].

The Hosein (2021) work was a mathematical model of the automobile insurance claim forecasting with a specific emphasis on the theoretical trade-off between personalization and confidence. The analysis of the study was quantitative in nature and measured the strength of claim estimates that can be gathered with varying levels of personalization to provide a basis in the development of personalized premium structure [17].

Ying et al. (2020) utilized one of the Genetic Algorithms (GA) to address the issue of setting up premium rates on occupational accident insurance. This was suggested to be used instead of the traditional actuarial techniques to better estimate the actual losses of certain industries [18].

III. METHODOLOGY

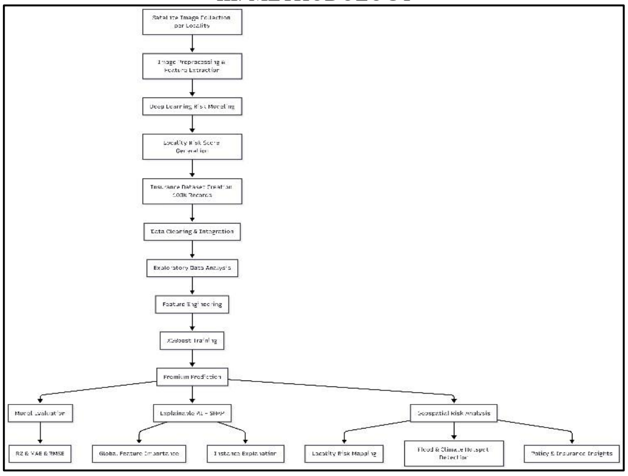

Fig 1: Process Flow Map

A. Dataset Preparation

The study was conducted across 125 distinct localities in Mumbai, India, representing heterogeneous urban morphologies including coastal zones, industrial belts, informal settlements, and high-density commercial areas. For each locality, eight high-resolution satellite images were collected to capture spatial variability and reduce sampling bias. Images were sourced to ensure consistent spatial resolution and coverage across zones. The multi-image strategy was adopted to provide a comprehensive representation of built-up density, road networks, green cover, water bodies, and structural patterns within each locality. This locality-wise image aggregation ensures robustness in downstream feature extraction and risk modelling [19].

B. Image Preprocessing and Feature Extraction

All satellite images underwent preprocessing to standardize input dimensions and improve computational consistency. Images were resized to 224×224 pixels and normalized before being fed into a deep convolutional neural network. A transfer learning approach was adopted using a pretrained ResNet50 architecture as the backbone model. The final classification layer was removed to extract deep feature embeddings from each image. For each locality, the feature representations obtained from the eight images were aggregated using mean pooling to generate a single localitylevel embedding vector. This aggregation mechanism ensured that the spatial diversity of each locality was encoded into a unified representation [20].

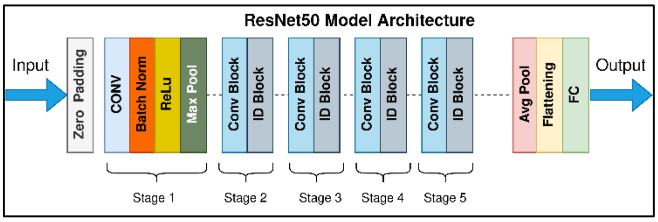

Fig 2. ResNet-50 Model Architecture Diagram

C. Urban Risk Score Generation

The aggregated locality embeddings were passed through a fully connected regression layer to produce a continuous urban risk score for each locality. The urban risk score is intended to capture composite environmental vulnerability, including inferred structural density, proximity to potential flood zones, industrial exposure, and vegetation scarcity. These scores were normalized to a bounded scale to enable integration with individual-level attributes. The resulting risk metric represents a satellite-derived proxy for spatial urban risk heterogeneity across Mumbai [21].

D. Insurance Dataset Construction and Feature Integration

An insurance dataset comprising over 100,000 policy-level records was constructed to evaluate the influence of urban risk on premium prediction. Each record was associated with one of the 125 localities and incorporated three primary categories of variables: (i) individual health attributes such as age, BMI, smoking status, alcohol consumption, chronic disease history, exercise frequency, and family medical background; (ii) socio-economic and property-related factors including annual income, property value, building age, and crime exposure; and (iii) urban-environmental indicators such as flood zone classification, industrial exposure level, air quality index, population density index, and the derived urban risk score. This integrated feature design enables simultaneous modeling of personal health risk and spatial urban vulnerability [22].

E. Predictive Modeling Framework

The insurance premium prediction task was formulated as a supervised regression problem. The dataset was partitioned into training and testing subsets using an 80:20 split to ensure generalization assessment. Multiple regression algorithms were implemented, including Linear Regression, Random Forest Regressor, Gradient Boosting, and XGBoost. These models represent diverse learning paradigms, ranging from linear parametric modeling to ensemble-based and gradient boosting techniques. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). Comparative evaluation enabled identification of the most effective approach for integrating urban and health risk determinants in premium estimation [23].

F. Explainable Artificial Intelligence Integration

To ensure transparency and interpretability in premium determination, explainable AI techniques were incorporated into the modeling pipeline. SHAP (SHapley Additive exPlanations) was used to quantify global feature importance and assess the marginal contribution of each predictor to premium outcomes. Additionally, LIME (Local Interpretable Model-agnostic Explanations) was employed to generate local explanations for individual predictions. These interpretability mechanisms enhance trust, regulatory compliance, and model accountability by clearly identifying how urban and health variables influence insurance pricing decisions [24,25].

G. Evaluation Strategy

The proposed framework was evaluated along three dimensions: predictive performance, interpretability, and practical scalability. Predictive accuracy was assessed using standard regression metrics, while interpretability was examined through consistency of SHAP and LIME explanations. Scalability was considered in terms of integrating satellite-derived urban intelligence with largescale insurance datasets. This evaluation design ensures both methodological rigor and real-world applicability in datadriven insurance underwriting

IV. RESULTS

A. Exploratory Data Analysis Results

Exploratory Data Analysis (EDA) reveals pronounced spatial heterogeneity in urban risk indicators across fine-grained localities of Mumbai. Environmental variables such as Air Quality Index (AQI), climate risk score, coastal proximity, and urban flood susceptibility display substantial intra-city variability, particularly across low-lying coastal wards and high-density built-up zones. Localities with reduced green cover and higher industrial or traffic concentration exhibit elevated environmental exposure levels. Health-related indicators, including respiratory disease prevalence and waterborne infection incidence, are notably higher in regions characterized by poor drainage infrastructure and chronic pollution exposure. Correlation analysis further indicates that environmental risk scores, flooding vulnerability, traffic density, and health burden metrics are positively associated with higher insurance premium values. These findings empirically validate the inclusion of geospatial and environmental determinants within the proposed climateaware premium prediction framework, reinforcing the necessity of locality-sensitive modeling in megacity insurance analytics.

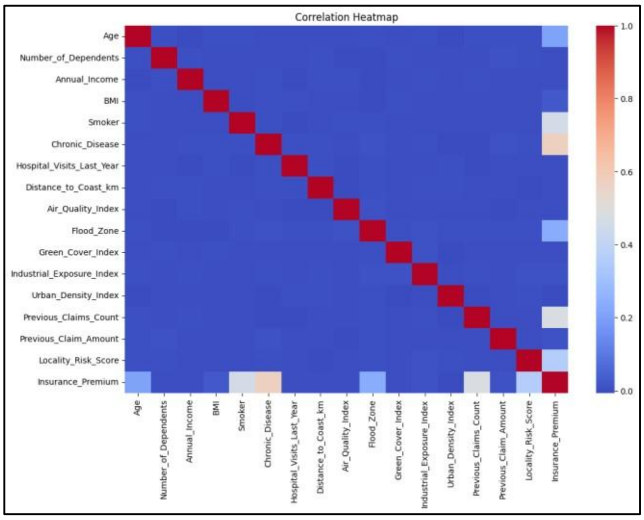

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Fig 3. Correlation Matrix

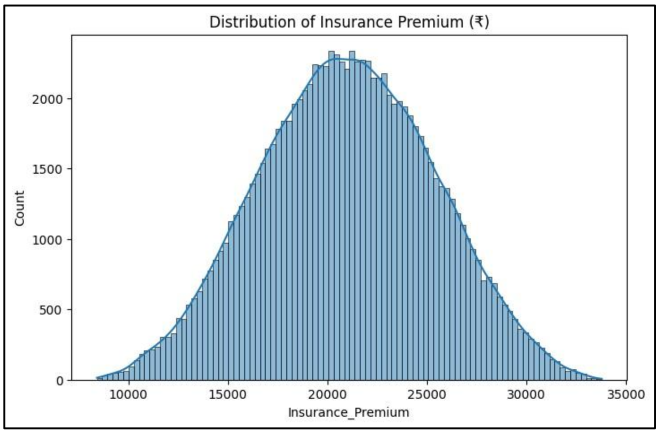

Fig 4. Insurance Data Distribution Table

B. Machine Learning Model Performance The XGBoost-based regression model demonstrates strong predictive capability in estimating insurance premiums. The model achieves an R^2 score of 0.9997, indicating that 99.97% of the variance in premium values is explained by the model, along with a Mean Absolute Error (MAE) of approximately ₹51, reflecting minimal prediction deviation. These results confirm the effectiveness of XG-Boost in capturing complex nonlinear interactions among multidimensional urban risk factors while maintaining high accuracy and stability across diverse metropolitan regions.

In addition to XGBoost, Random Forest and Gradient Boosting regression models were also implemented for comparative evaluation. Both ensemble methods exhibited competitive performance with high R^2 scores and low monetary error margins, reinforcing the robustness of treebased ensemble learning in premium prediction tasks. However, Linear Regression was excluded from final deployment despite achieving an R^2 score close to 1.0, as such perfect linear fit indicates potential multicollinearity, data leakage, or overfitting due to strong deterministic relationships among features. Given the nonlinear and spatially heterogeneous nature of urban risk indicators, linear modeling assumptions were deemed unsuitable for reliable real-world insurance pricing applications.

Model	MAE (₹)	RMSE (₹)	R^2 Score
Random Forest	81.11	103.15	99.94 %
Gradient Boosting	125.83	158.17	99.84 %
XG-Boost	51.52	66.02	99.97 %

Table 1.

C. Explainable AI (SHAP) Results

SHAP- and LIME-based explainability mechanisms provide transparent and interpretable insights into the behavior of the proposed XGBoost-driven insurance premium prediction framework across fine-grained localities of Mumbai. Global
SHAP feature importance analysis identifies environmental pollution levels (AQI), climate risk indices, urban flooding susceptibility, coastal exposure, health burden indicators, and infrastructure quality as dominant contributors to premium variation across neighborhoods. These findings reinforce the spatial and climate-sensitive nature of premium determination within a megacity context. At the instance level, SHAP explanations illustrate how locality-specific environmental and health risk combinations influence individual premium estimates, capturing nonlinear interactions among multidimensional urban risk factors. Complementarily, LIME provides case-specific, localized linear approximations that further validate the contribution and directional impact of key predictors for particular policyholders or neighborhoods. Together, SHAP and LIME enhance transparency, interpretability, and auditability of the predictive system, thereby supporting regulatory compliance and trust in climate-aware insurance pricing applications in emerging metropolitan regions.

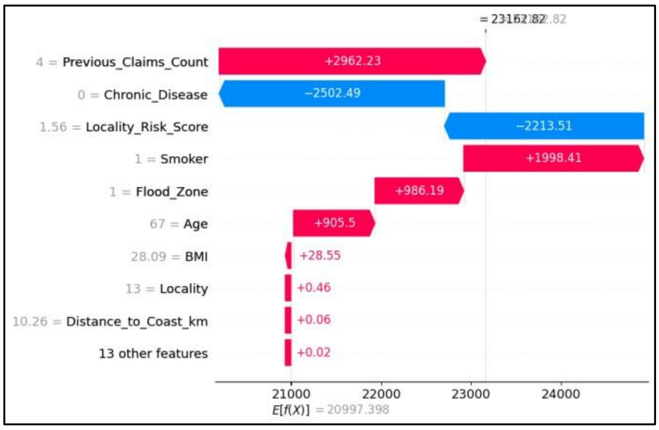

Fig 5. SHAP Analysis (Explainable AI)

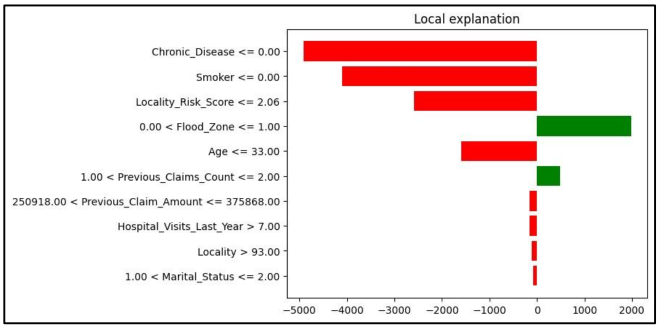

Fig 6. LIME Explanation (Explainable AI)

D. Geospatial Mapping Results

Geospatial visualization of predicted insurance premiums across fine-grained localities of Mumbai reveals pronounced intra-city spatial heterogeneity in risk distribution. Premium heatmaps highlight concentrated high-risk clusters in lowlying coastal belts, flood-prone wards, high-density built-up zones, and areas characterized by elevated air pollution and traffic congestion. These premium hotspots spatially coincide with localities exhibiting higher climate risk scores, urban flooding susceptibility, and greater health burden indicators, reinforcing the climate-sensitive structure of the predictive framework. In contrast, comparatively lower premium zones are observed in neighborhoods with stronger infrastructure quality, improved drainage systems, higher green cover, and relatively lower environmental exposure levels. The spatial distribution patterns substantiate the necessity of integrating geospatial risk intelligence with explainable machine learning models, thereby enabling locality-aware, climateresilient insurance pricing mechanisms within megacity environments such as Mumbai.

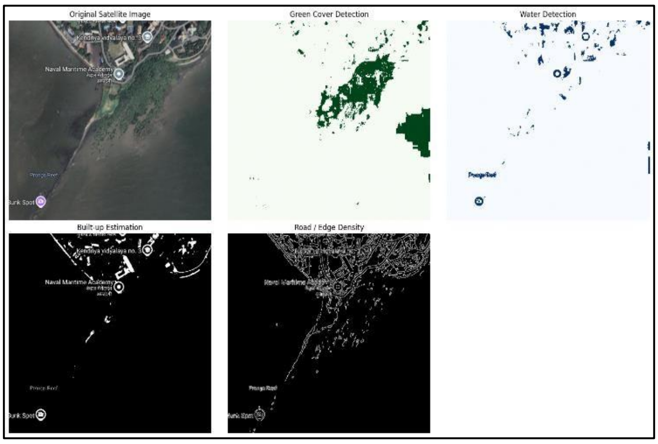

Fig 7. Geo-Spatial Map Showing Navy Nagar Locality of Mumbai City

V. CONCLUSION & FUTURE DIRECTION

This study presents an explainable machine learning framework for insurance premium prediction that integrates multidimensional urban risk factors, including environmental exposure, climate change impacts, urban flooding susceptibility, public health indicators, infrastructure quality, and geospatial characteristics. The XGBoost-based model achieves strong predictive performance with an R^2 score of 0.9997 and a Mean Absolute Error of approximately ₹51, demonstrating its effectiveness in capturing complex nonlinear relationships. The incorporation of SHAP-based explainability ensures transparency and interpretability of premium decisions, while geospatial hotspot mapping provides actionable locality-level insights into urban risk variability across Mumbai. Together, these components highlight the potential of combining explainable AI and geospatial analytics to support accurate, fair, and accountable insurance pricing in urban environments..

Future work can extend the proposed framework by incorporating temporal dynamics such as seasonal climate variability, long-term climate change projections, and evolving urban infrastructure conditions. Integration of realtime environmental and health data streams and historical insurance claims data could further enhance predictive robustness and practical applicability. Additionally, expanding the framework to include policy simulation and scenario analysis would enable insurers and policymakers to assess the impact of climate adaptation measures and public health interventions on insurance affordability. Extending the approach to rural and semi-urban regions and exploring advanced Geo-AI techniques also present promising directions for future research. The framework can also be extended to other major metropolitan cities in India, such as Delhi-NCR, Bengaluru, Chennai, Hyderabad, and Kolkata, to enable comparative urban risk assessment and cross-city premium modelling. Extending the approach to rural and semi-urban regions and exploring advanced Geo-AI techniques also present promising directions for future research.

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