Project Report On

Landslide Prediction using XAI and Spatio-Temporal Knowledge Graph

Submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology

in

Computer Science and Engineering

By
Kristin Elizabeth Binu (U2003122)
Lakshmi Thampi Anoopkumar (U2003123)
Maria Sunil (U2003128)
Merin Jose (U2003133)

Under the guidance of

Dr. Preetha K. G.

Department of Computer Science and Engineering
Rajagiri School of Engineering & Technology (Autonomous)
(Parent University: APJ Abdul Kalam Technological University)
Rajagiri Valley, Kakkanad, Kochi, 682039
April 2024

CERTIFICATE

This is to certify that the project report entitled ***"Landslide Prediction using XAI and Spatio-Temporal Knowledge Graph"*** *is a bonafide record of the work done by* ***Kristin Elizabeth Binu (U2003122), Lakshmi Thampi Anoopkumar (U2003123), Maria Sunil (U2003128), Merin Jose (U2003133)****, submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2023-2024.*

Dr. Preetha K. G.
Project Guide
Professor & HoD
Dept. of CSE
RSET

Dr. Tripti C.
Project Coordinator
Associate Professor
Dept. of CSE
RSET

Dr. Preetha K. G.
Head of the Department
Professor
Dept. of CSE
RSET

ACKNOWLEDGMENT

We wish to express our sincere gratitude towards **Prof. (Dr.) P. S. Sreejith**, Principal of RSET for providing us with the opportunity to undertake our project, ”Landslide Prediction using XAI and Spatio-Temporal Knowledge Graph”.

We are highly indebted to our project coordinator, **Dr. Tripti C.**, Associate Professor, Dept. of CSE, for her valuable support.

It is indeed our pleasure and a moment of satisfaction for us to express our sincere gratitude to our project guide **Dr. Preetha K. G.**, Head of the Dept. of CSE, for her patience and all the priceless advice and wisdom she has shared with us.

Last but not the least, we would like to express our sincere gratitude towards all other teachers and friends for their continuous support and constructive ideas.

Kristin Elizabeth Binu

Lakshmi Thampi Anoopkumar

Maria Sunil

Merin Jose

Abstract

Landslides present an imminent danger to human life and infrastructure, making their prediction a critical task in disaster management. A novel method for landslide prediction that combines Explainable Artificial Intelligence (XAI) and Spatio-Temporal Knowledge Graphs (STKGs) to enhance landslide prediction and understanding.

Our proposed system leverages XAI techniques to create models that not only predict the likelihood of landslides but also provide interpretable explanations for these predictions. This interpretability is crucial for decision-makers to take timely and informed actions. By utilizing STKGs, we integrate diverse data sources, including topography, weather patterns, historical landslide events, and land-use changes, into a unified knowledge graph.

This STKG enables us to capture complex relationships and temporal patterns that contribute to landslide occurrences. Machine learning models, trained on this enriched dataset, deliver accurate predictions while also providing insights into the underlying causes. Additionally, the STKG facilitates real-time monitoring and adapts to changing environmental conditions, making it a valuable tool for early warning systems.

The fusion of XAI and STKGs offers a comprehensive and transparent solution for landslide prediction, enhancing both the accuracy and trustworthiness of predictive models. Our research contributes to more effective disaster preparedness and response, ultimately reducing the impact of landslides on communities and the environment.

Contents

List of Abbreviations

Table 2: List of Abbreviations and Their Expansions

Abbreviation	**Expansion**
DM	Direct Mapping
DPKG	Disaster Prediction Knowledge Graph
FOL	First Order Logic
GNN	Graph Neural Network
ITEM-CF	Item Collaborative Filtering
KGE	Knowledge Graph Embedding
KGLP	Knowledge Graph Link Prediction
NER	Named Entity Recognition
NMF	Non-negative Matrix Factorization
OWL	Web Ontology Language
RDF	Resource Description Framework
SVD	Singular Value Decomposition
SWRL	Semantic Web Rule Language
TransE	Translation-based Embedding
TransR	Translation-based Embedding with Rescaling
XAI	Explainable Artificial Intelligence

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background (Preamble)

In recent years, the escalating frequency and impact of landslides have underscored the critical need for advanced predictive models to mitigate the devastating consequences of these natural disasters. Recognizing the complexity of landslide dynamics and the importance of transparent decision-making, we embark on a pioneering journey into the realm of Explainable Artificial Intelligence (XAI) coupled with Spatio-Temporal Knowledge Graphs. By harnessing the power of XAI, the aim is to forecast landslides and provide clear insights into the underlying factors influencing these events.

Landslides threaten human lives, infrastructure, and the environment, demanding innovative solutions for early detection and prediction. Traditional methods often fall short in capturing the intricate interplay of factors contributing to landslide occurrence. This has spurred the integration of artificial intelligence, specifically XAI, to not only predict landslides but to unravel the intricate relationships within the data, offering interpretable results crucial for informed decision-making.

The challenge lies in developing a predictive model that not only accurately anticipates landslide events but also provides stakeholders with a transparent understanding of the driving factors. Achieving this necessitates the incorporation of spatio-temporal knowledge graphs, enabling the representation of complex relationships among geographical, meteorological, and geological variables over time.

The combination of XAI technologies with spatio-temporal knowledge graphs holds immense power in revolutionizing landslide prediction. By elucidating the decision-making process of our models, we empower authorities, researchers, and communities to make informed choices in real time, enhancing preparedness and reducing the impact of these natural disasters. The goal is to not only advance the state-of-the-art in landslide prediction but also to foster a new era of transparent and accountable AI applications in the domain of natural disaster management.

1.2 Problem Definition

The project aims to develop a Landslide Prediction system utilizing Spatio-Temporal Knowledge Graphs and Explainable AI to enhance our understanding of landslide dynamics, provide accurate predictions, and offer interpretable insights into the factors contributing to landslide occurrences.

1.3 Scope & Motivation

Landslide Prediction using Explainable Artificial Intelligence (XAI) and Spatio-Temporal Knowledge Graph presents a vast scope for advancing the accuracy and interpretability of landslide risk assessments. By integrating diverse spatio-temporal data sources into a comprehensive knowledge graph, the approach aims to capture the complex relationships influencing landslide occurrences. The scope extends to the development of machine learning models, leveraging deep learning techniques to extract relevant features from satellite imagery, weather patterns, geological data, and historical landslide records. The interpretability introduced by XAI methods addresses the crucial need for transparent insights into model predictions, facilitating better risk communication. Additionally, the scope encompasses the continuous improvement of predictive models, allowing for adaptability to changing environmental conditions and real-time data integration.

The motivation behind Landslide Prediction using XAI and Spatio-Temporal Knowledge Graph lies in the urgent need to enhance landslide risk mitigation strategies. Traditional methods often lack the ability to comprehensively analyze the intricate spatio-temporal factors influencing landslides. XAI fills this void by offering understandable insights into the decision-making processes of intricate models, cultivating trust among stakeholders. The motivation extends to the potential for early warning systems that can significantly reduce the impact of landslides by providing timely alerts to at-risk areas. Moreover, the integration of diverse data sources into a knowledge graph enables a holistic understanding of the dynamic environmental conditions leading to landslides, thereby motivating the development of predictive models that can adapt and improve over time. Overall, the motivation is rooted in the aspiration to minimize the societal and environmental impacts of landslides through advanced, explainable, and adaptive prediction methodologies.

1.4 Objectives

- Minimizing risk and damage by providing early warnings.
- Understanding triggering factors.
- Developing effective mitigation strategies, and safeguarding vulnerable communities and infrastructure.

1.5 Assumptions & Challenges

1.5.1 Assumptions

- Data used for model development is accurate, complete, and representative of the study area.
- The underlying geological and environmental conditions are relatively constant over the prediction period.

1.5.2 Challenges

- Unavailability of large datasets for more accurate result.
- Handling and processing of large datasets efficiently requires high end systems.
- Landslide datasets can suffer from data quality issues, such as missing or inconsistent data, incorrect labels, or outdated information.

1.6 Societal / Industrial Relevance

The societal relevance of a landslide prediction project using a knowledge graph and Explainable Artificial Intelligence (XAI) lies in its potential to safeguard human lives and communities inhabiting landslide-prone areas. By providing early warnings and transparent insights into the factors influencing landslide susceptibility, the project empowers residents and authorities to take proactive measures, fostering resilience and preparedness. This initiative contributes directly to public safety, mitigates the impact of natural disasters, and promotes sustainable living in regions susceptible to landslides. Beyond immediate safety concerns, the project holds the promise of positively influencing land-use planning, emergency response strategies, and community awareness, thereby creating a more secure and informed societal environment.

1.7 Organization of the Report

Chapter 1 deals with an overview of what XAI and Spatio-Temporal Knowledge Graph is, its scope and motivation and the various objectives to predict landslides.
Chapter 2 deals with the various methods taken in order to create a literature survey on XAI and Spatio-Temporal Knowledge Graph.
Chapter 3 gives a brief outline of software and hardware requirements.
Chapter 4 explains the system overview along with module division and work breakdown.
Chapter 5 concludes by comparing various methods to implement XAI Spatio-Temporal Knowledge Graph with existing technologies and drawing their conclusions.

Chapter 2

Literature Survey

2.1 A method to predict landslides using Multi-Source Data and Spatio-Temporal Knowledge Graph [1]

The following steps are part of the methodology employed in predicting landslides using Multi-Source Data and Spatio-Temporal Knowledge Graph:

Data Organisation: A semantic structure is used to organize environmental data from remote sensing to increase efficiency. The approach groups environmental data from remote sensing according to a semantic structure to increase efficiency. This entails training the candidate models and gathering unavailable data into the knowledge graph. By structuring the data in a semantic knowledge graph, the method aims to enhance the organization and utilization of remote sensing environmental data, thereby contributing to the overall effectiveness of the landslide prediction process.

Establishing inference guidelines: For understanding environmental similarity assessments and candidate model selection it is necessary to lessen the influence of sample scarcity on landslide prediction outcomes [6]. To mitigate the sample scarcity impact on landslide prediction outcomes, inference methods are established for candidate model selection. To facilitate model training, this stage assesses the historical landslide data. The knowledge graph is used to analyze the environmental similarities within the area if the quantity is insufficient. The model most closely resembles the study site and is then chosen as the candidate for landslide prediction. In this way, the problem of limited historical data is tackled, and the precision of landslide forecasting in areas with low sample sizes is improved.

Improve model applicability: To enhance the model's applicability environmental feature information is incorporated into the machine learning approach. Data from remote sensing drive this. Reasoning rules are built on the basis of spatio-temporal knowledge graphs[7]. These results determine environmental similarity analysis and candidate models are then chosen for landslip prediction. The method attempts to improve the overall performance of the landslip prediction models and increase the predictive power for sample-scarcity areas by incorporating environmental knowledge into the machine learning process.

Testing: Efficacy of a model cannot be compromised. Demonstration of the method's efficacy and its potential for disaster analysis in geological hazard management is done using tests. This entails using the workflow based on knowledge graphs to create a landslide susceptibility map in an actual setting. After the candidate models have been trained using the methodology, the model that most closely resembles the study area is chosen to be used for landslide prediction. By contrasting the outcomes of the standard process with the workflow with extra knowledge graph steps, the efficacy of the approach is assessed. The results of the studies show that the suggested strategy performs better than conventional machine learning techniques, increasing the F1 score and enhancing processing efficiency.

2.2 Construction of Knowledge Graphs and Application in Geosciences [2]

A systematic modeling process is followed akin to database construction as shown in Figure 2.1. It begins by identifying the subject domain and research needs, followed by the design of a conceptual model using tools like CmapTools. Subsequently, logical and physical models contribute representation and assertions, while also taking into account the choice of coding languages, serialization formats (e.g., RDF/XML, Turtle, JSON-LD), and platforms such as DOGMA. The KG is then deployed as a service for community reuse. Many geoscience KGs, including mineral classification schema, SWEET ontology, and GeoCore ontology, have been constructed through this method [8]. The bottom-up approach relies on crowdsourced data from sources like social media and literature legacy. Leveraging Web content and an observation-driven approach, this method has gained traction with the growth of social media and open-access literature. Techniques like Hadoop processing of geotagged data in Flickr and natural language processing for geoscience literature have demonstrated the effectiveness of the bottom-up approach. Despite its ability to process vast datasets rapidly, a challenge lies in ensuring precise logical representation and assertions in the resulting KG. Often, domain experts and knowledge engineers must specify these details, highlighting the potential for reusing existing KGs for improved accuracy and efficiency in the bottom-up construction approach.

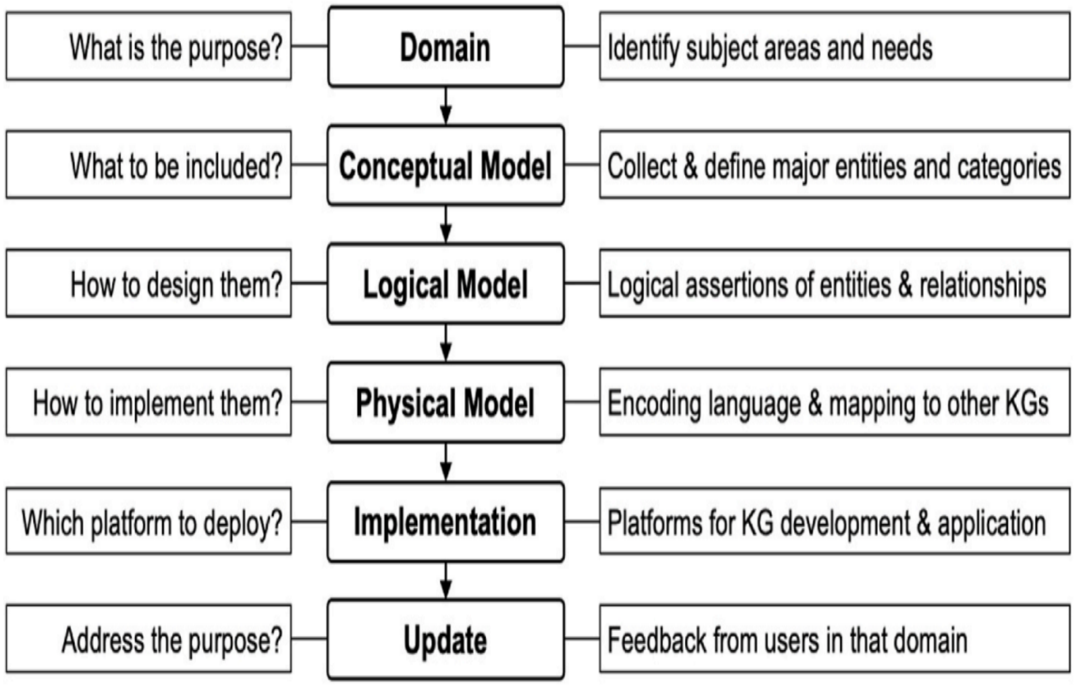


Figure 2.1: A top-down method for creating and implementing knowledge graphs.

2.3 A method to construct Disaster Prediction Knowledge Graph from various Spatio-Temporal Information [3]

A sophisticated understanding of multi-source spatio-temporal data is imperative for effective decision-making. Knowledge Representation Language, utilizing computer symbols, is a scientific beacon to encode and mark objectively existing knowledge [9]. Within the Dynamic Prediction Knowledge Graph (DPKG), the conceptual layer establishes a logical structure for intricate relationships, ensuring consistency in semantic concepts. Disaster prediction inference rules fortify this framework, employing First-Order Logical and Production Inference rules and the design of the instance layer, which extracts knowledge from diverse sources for adaptive prediction of disasters like forest fires and geological landslides.

Implementing knowledge representation language: A representation language using computer symbols to objectively mark the existing knowledge in a scientific manner to aid in semantic thinking. Triples inside the RDF are the most widely utilized form of knowledge representation. Every bit of information can be expressed using the triple structure of (subject, predicate, object). OWL is the language of knowledge representation used in this investigation.

Designing the Conceptual Layer: Semantic concepts and their relationships are described in this layer. Semantic linkages between ideas, such as subordinate and attribute relationships, create a hierarchical structure [10]. A concept triple interconnection network is built to ensure semantic consistency across several spatio-temporal data sources.

Construction of Disaster Prediction Inference Rules: FOL formalizes hierarchical and attribute relationships, crucial in disaster prediction ontologies, using OWL language, enabling first-order logical reasoning for effective modeling in mathematics, philosophy, linguistics, and computer science. To overcome first-order logic limitations, we use Semantic Web Rule Language (SWRL) to extend OWL axioms with Horn-like rules, enhancing rule expression for the Disaster Prediction Knowledge Graph (DPKG), exemplified by a rule linking properties of a tree and those of a forest fire risk-level to infer the likelihood of that tree to cause a forest fire.

Designing the Instance Layer: The design of the instance layer involves extracting knowledge from diverse data sources through advanced methods such as deep learning, converting the information into triples based on specific representations, and storing these triples in the GraphDB for effective dynamic disaster prediction, specifically focusing on forest fires and geological landslides.

- Extracting knowledge using unstructured information: Depends on land cover data with a high spatiotemporal resolution (0.8 m resolution) from satellite remote sensing photos. The spatial distribution of disaster-prone objects are extracted using deep learning techniques. This data is then transformed into triplets according to predetermined spatiotemporal and professional attribute representations, and the triplets are then stored in the database.

- Extracting knowledge using semi-structured information: The method involves transforming various types of raster inputs into vector outputs representing surface structures such as litho-stratigraphical age, fault, and distribution, which are then transformed into vector geographic information stored in triples within the GraphDB. Apart from this, we also consider some reasoning criteria which are later discussed in this section.

- Extracting knowledge using structured information: The barometrical information utilized for the prediction of disasters is done by mapping the relationship to spatiotemporal attributes. To enhance reasoning speed and avoid processing a large volume of irrelevant data, only the spatial information of potential disasters is converted into triples and then maintained in the database.

- Extracting knowledge using disaster prediction reasoning criterion [11]: Reasoning criteria that we consider are H - index calculation, effective rainfall, and landslide strength.

  - H - index: This parameter is calculated by multiplying probabilities of space, time, and frequency of landslide disasters that occur within a given time frame.

  - Effective Rainfall: The effective rainfall in the region is taken into account for the previous days' contributions to the total amount of rain that causes the landslide. The contribution rate to the geological landslide increases if rainfall at a later time is considered.

- Landslide strength: To represent the destructive force of the landslide we use the landslide strength. It involves considering the magnitude of the product of landslide volume and sliding velocity.

2.4 Landslide Identification using FKGRNet Model [4]

FKGRNet, a novel approach for landslide identification in remote sensing images addresses the challenge of multimodal landslide data. As seen in Figure 2.2, this technique utilizes a knowledge graph[12] in conjunction with the well-known image recognition tool ResNet model[13] to identify landslides. Two feature fusion techniques—feature splicing and feature classifier—are suggested to aid in efficient integration. The feature classifier method creates a prior probability vector. This is done using Bayesian equations and proves beneficial when the ResNet model encounters difficulties in accurate recognition. On the other hand, the feature splicing approach directly combines ResNet-extracted features and knowledge graph vectors, demonstrating superior performance in accuracy and F1-score for landslide recognition.

The experimental findings highlight the effectiveness of FKGRNet over alternative deep learning models and a baseline model, demonstrating its superior performance across various network depths and fusion techniques. This approach offers valuable insights into building a comprehensive knowledge graph concerning landslides, encompassing diverse entities and their relationships. Utilizing the TransE model[14] for knowledge representation learning and FKGRNet, missing triads in the knowledge graph can be predicted more easily by mapping entities and their relationships to a lower-dimensional vector space. With the use of landslide information, FKGRNet is able to more precisely recognize landslide occurrences in remote sensing photos, leading to improved performance and a greater comprehension of the interrelated processes causing landslides.

Additionally, the method delves into the pre-processing and feature extraction steps for landslide image data using the ResNet model. It emphasizes the importance of data enhancement techniques and the utilization of residual blocks in ResNet for effective feature extraction. Overall, FKGRNet effectively utilizes landslide knowledge to improve the precision of detecting landslide events in remote sensing images. The fusion of the knowledge graph and ResNet accommodates multimodel landslide data, making it a promising approach for comprehensive landslide identification.

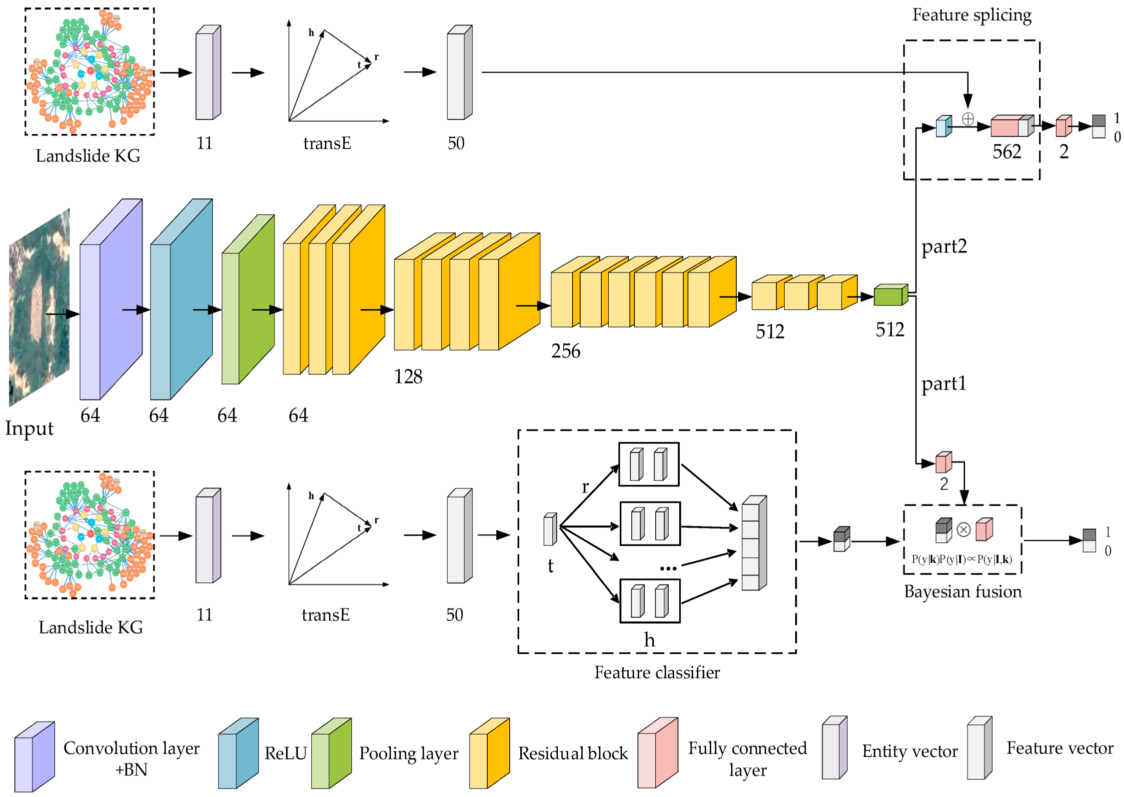


Figure 2.2: Combined feature classifier and feature splicing model

2.5 Landslide Prediction and Understanding Landslide Events With Explainable AI [5]

The study focuses on predicting landslides using machine learning models and explainable artificial intelligence techniques.

The study collects static and dynamic features related to the land description, rainfall, temperature, wind, etc., over several years and a large territory. This includes rain gauge data, cumulative rainfall, mean rain values, standard deviation values, and other relevant metrics.

Convolutional Neural Networks, or CNNs, are particularly useful for evaluating spatial and picture data because of their ability to learn spatial local features from input data. Four pairs of convolutional and pooling layers make up the CNN model architecture, which is followed by fully connected layers for classification. Convolution, as opposed to general matrix multiplication, is used in at least one of CNN's layers to capture both global and local characteristics, improving accuracy and efficiency. Using CNN's capacity to learn and extract features from the input data, it is used here to assess and classify spatial data linked to landslides.

Also, a particular application of the Gradient Boosting methodology that is well-known for its accuracy and efficiency in identifying the optimal tree model is the eXtreme Gradient Boosting (XGBoost) method. It uses a large number of the forest's trees for classification, with max depth = 40 designating each tree's maximum depth. XGBoost is well-known for its dependability in predictive modeling and resilience against false alarms. With respect to other models and state-of-the-art references, XGBoost is used in this study's landslide prediction context and yields better results in terms of sensitivity, mean absolute error, mean squared error, true skill statistic, overall accuracy, and root mean squared error.

In the study, Explainable Artificial Intelligence (XAI) techniques were utilized to gain a deeper understanding of the predictive model outputs and feature relevance in the context of landslide prediction. Specifically, the study applied Shapley Additive Explanations (SHAP) to globally and locally assess the feature relevance for the XGBoost model, which achieved the best results in terms of predictive accuracy.

By leveraging XAI techniques, the study aimed to enhance the interpretability of the predictive model, identify the best features for short-term predictions, and assess their impact on both local cases and the global prediction model. The application of XAI in the study provided a deeper understanding of the factors driving the landslide prediction model's outputs, contributing to the transparency and trustworthiness of the AI-based predictive system.

2.6 Summary and Gaps Identified

2.6.1 Summary

The proposed methodologies for landslide prediction, as outlined in the provided sections adopt a data-driven approach. The method begins with the organization of environmental data using a semantic structure, aiming to improve efficiency by addressing missing data through knowledge graph integration. Guidelines for inference are developed with a focus on environmental similarity analysis in the absence of sufficient historical data. By adding environmental feature data and using reasoning rules derived from the Spatio-Temporal Knowledge Graph, the applicability of the model is increased. The final step involves testing the efficacy of the method through real-world scenarios, such as producing landslide susceptibility maps, and demonstrating its potential for practical application and disaster analysis.

Knowledge Graph development in geosciences is explored, focusing on two primary strategies: the top-down and bottom-up approaches. The approach involves a systematic modeling process, starting with the identification of the subject domain and research needs, leading to the deployment of the Knowledge Graph as a service for community reuse. The bottom-up approach relies on crowdsourced data, leveraging web content and observation-driven methods. The challenges of ensuring precise logical representation in the resulting Knowledge Graph are acknowledged, with the potential for reusing existing graphs to enhance accuracy in the bottom-up construction approach. Overall, these sections contribute to advancing the understanding of landslide prediction by incorporating semantic structures, Spatio-Temporal Knowledge Graphs, and data-driven methodologies.

Despite these advancements, various gaps have been identified in the current state of the art. These gaps include the requirement for further research on integrating multi-source spatio-temporal data into Knowledge Graphs for predicting disasters. Additionally, there is a call for more comprehensive studies evaluating the effectiveness and generalizability of the proposed methodologies in real-world scenarios. The scalability of these methods across different geographical regions and the consideration of ethical and privacy aspects in landslide prediction systems also represent important areas for future research. Lastly, the integration of Explainable AI in the landslide prediction process is a promising avenue, but more work is needed to enhance the interpretability and transparency of the models for practical deployment and decision-making.

2.6.2 Gaps Identified

Integration: There is a need for further research and development in effectively integrating diverse sources of spatio-temporal data in the context of landslide prediction. The existing methodologies briefly touch upon the utilization of remote sensing, meteorological, and terrain data, but there is a lack of detailed exploration into the challenges and optimal strategies for harmonizing these varied datasets seamlessly.

Evaluation in Real-World Scenarios: The studies discuss the methodologies and present their effectiveness through experiments and tests. However, there is a gap in the depth of real-world scenario evaluations. Comprehensive assessments in diverse geographical settings and under varying conditions are necessary to establish the generalizability and robustness of the proposed methodologies in practical applications.

Scalability Across Geographical Regions: The scalability of the proposed landslide prediction systems across different geographical regions is not extensively addressed. Landslide characteristics, environmental factors, and data availability can vary significantly across regions. It is crucial to investigate the adaptability and performance of these methodologies in various geographic contexts.

Ethical and Privacy Considerations: While the system overview briefly mentions ethical considerations, there is a gap in providing a detailed exploration of the ethical and privacy aspects associated with landslide prediction systems. Further research is needed to establish guidelines and frameworks for ensuring responsible use of the technology, especially when dealing with sensitive environmental and location-based data.

Explainability and Interpretability of AI Models: The integration of Explainable AI (XAI) techniques is highlighted as a positive step, but there is a need for more in-depth exploration. The studies mention the application of methods such as LIME and SHAP values, but a comprehensive discussion on the interpretability and explainability of the AI models in the context of landslide prediction is lacking. Future research should focus on enhancing the transparency of models for effective decision-making.

Addressing these identified gaps will contribute to the advancement of landslide prediction methodologies, making them more robust, applicable to diverse scenarios, and ethically sound for practical deployment.

2.7 Existing System

Existing methods for landslide prediction encompass a multifaceted approach, combining field-based surveys, geological investigations, and historical data analysis. Geologists conduct thorough on-site inspections to assess the geological and topographical features of an area, examining factors such as soil types, slope angles, and geological indicators that may signal susceptibility to landslides. Rainfall monitoring plays a crucial role, as heavy or prolonged rainfall can saturate the soil, leading to heightened instability. The use of remote sensing technologies, alongside Geographic Information System (GIS) tools, aids in the analysis of satellite imagery and aerial photographs, enabling the mapping and understanding of changes in land surfaces over time.

Historical data analysis provides valuable insights into past landslide events, allowing for the identification of patterns and contributing factors that enhance the understanding of long-term susceptibility. Ground-based instruments, including inclinometers and ground displacement sensors, are strategically deployed to monitor subtle ground movements, providing early indications of potential landslide activity. Hydrological modeling is employed to assess various factors, such as soil moisture, groundwater levels, and runoff patterns, as excessive water can significantly contribute to slope instability. While these methods offer valuable information, they often face limitations in precision and real-time monitoring capabilities, emphasizing the need for continued advancements in predictive techniques to enhance the overall effectiveness of landslide prediction.

Chapter 3

Hardware and Software Requirements

3.1 Hardware and Software Requirements

- System: 16GB RAM, 32 bit CPU
- Programming Languages: Python
- Machine Learning Frameworks: TensorFlow
- Explainable AI (XAI) Libraries: SHAP, LIME
- Geospatial Libraries: GeoPandas
- Integrated Development Environment (IDE): Jupyter Notebooks
- Knowledge Graph Construction: Neo4j

Chapter 4

System Architecture

4.1 System Overview (Proposed System)

The Landslide Prediction System employing Explainable Artificial Intelligence (XAI) and a Spatio-Temporal Knowledge Graph aims to address the challenges associated with accurate landslide prediction. The system's architecture integrates XAI techniques, such as LIME and SHAP values, enhancing model interpretability and transparency. Additionally, a Spatio-Temporal Knowledge Graph is constructed to capture dynamic environmental factors, providing a comprehensive representation of spatial and temporal data. Machine learning models, selected based on predictive performance, undergo training and validation, with real-time monitoring enabling early detection and alerting mechanisms for timely notifications. The user interface offers visualization of predictions, XAI explanations, and Knowledge Graph insights, while ethical considerations and scalability strategies are essential components of the system's design and deployment.

4.2 Architecture Diagram of the System

The proposed system involves a multi-step process aimed at leveraging machine learning techniques for landslide prediction or analysis as shown in Fig 4.1 The initial stages of the architecture focus on acquiring and preprocessing the data. Landslide-related data is collected and cleaned to ensure it is suitable for further analysis. The quality of the data at this stage significantly impacts the effectiveness of the subsequent steps.

Following data preprocessing, the system constructs a knowledge graph using the acquired and cleaned data. This graph represents the relationships and entities relevant to landslides. Entities may include geological features, weather conditions, and historical landslide occurrences, while relationships capture connections between these entities. Constructing a knowledge graph provides a structured and interconnected representation of the underlying factors contributing to landslides.

The knowledge graph undergoes an embedding process, where it is transformed into a vectorized form. This transformation is crucial for inputting the graph data into machine learning models. The vectorized representation enables efficient processing by converting complex relationships in the graph into numerical vectors that can be understood by machine learning algorithms.

Machine learning models are then employed for classification, involving the selection of black box models. These models utilize the vectorized knowledge graph as input, incorporating feature importance data to highlight the significant factors influencing the predictions.

An essential aspect of the proposed system is its focus on explainability. To interpret the predictions of the random forests, an explainable AI model is implemented. Transparent algorithms provide insights into the reasons behind specific model outputs by aiding in understanding the decision-making process.

The final stages involve visualizing the model outputs using the explainable AI model. This visualization allows for a thorough examination of the results, facilitating the interrogation of the black box model. Additionally, subjective evaluation is performed to ensure that the outputs align with human expectations and standards. This step introduces a human-centric perspective to validate the model's predictions against domain knowledge and common sense, enhancing the overall reliability of the system. In summary, the proposed architecture integrates data preprocessing, knowledge graph construction, machine learning models, explainability, and subjective evaluation to create a comprehensive system for landslide prediction or analysis.

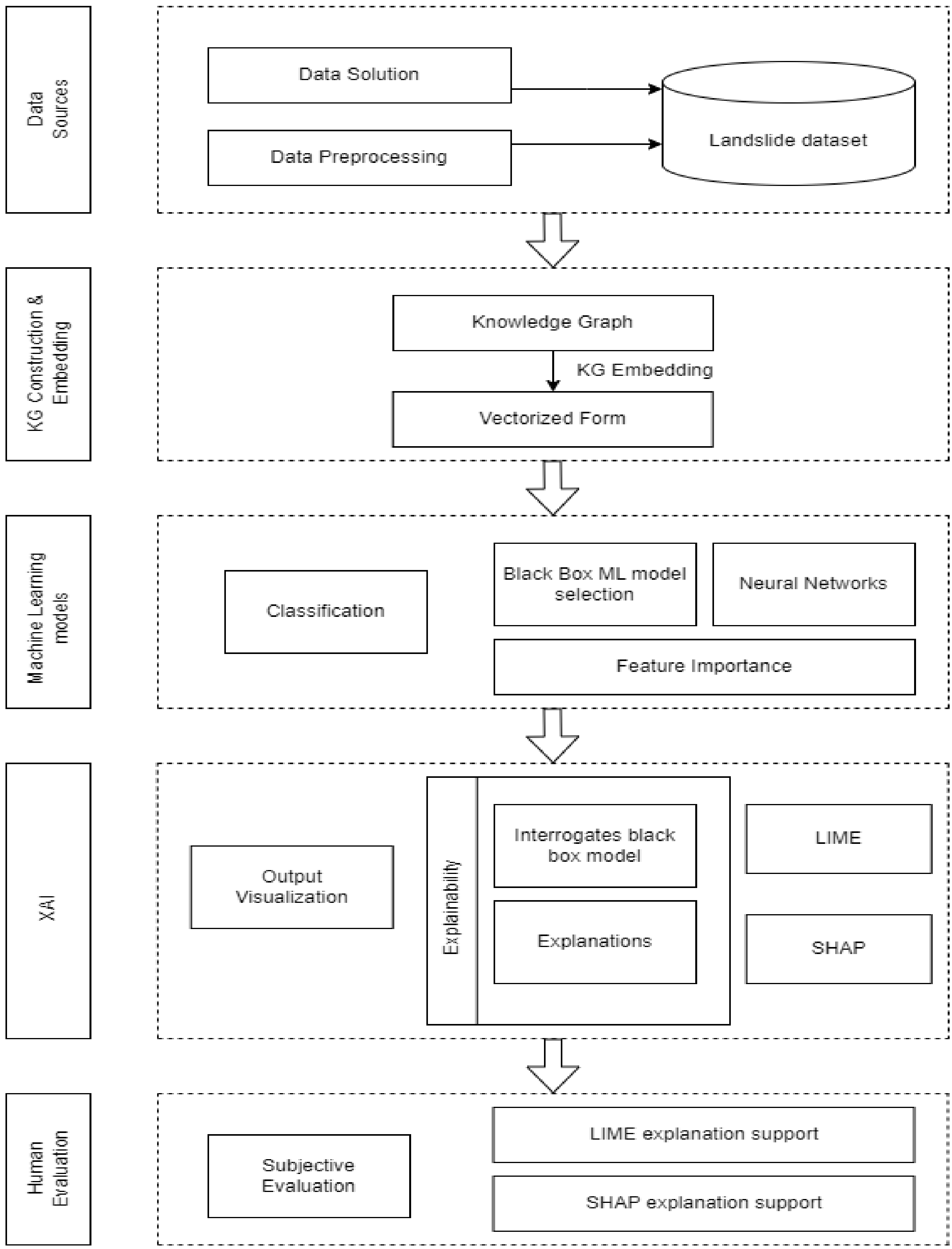


Figure 4.1: Architecture Diagram

4.3 Sequence Diagram

Figure 4.2 explains the sequence of actions followed in the landslide prediction scenario, providing a dynamic view of the system's behavior. Actors or objects are depicted as vertical lifelines, and the horizontal arrows between them represent messages passed during the execution of a particular use case or operation.

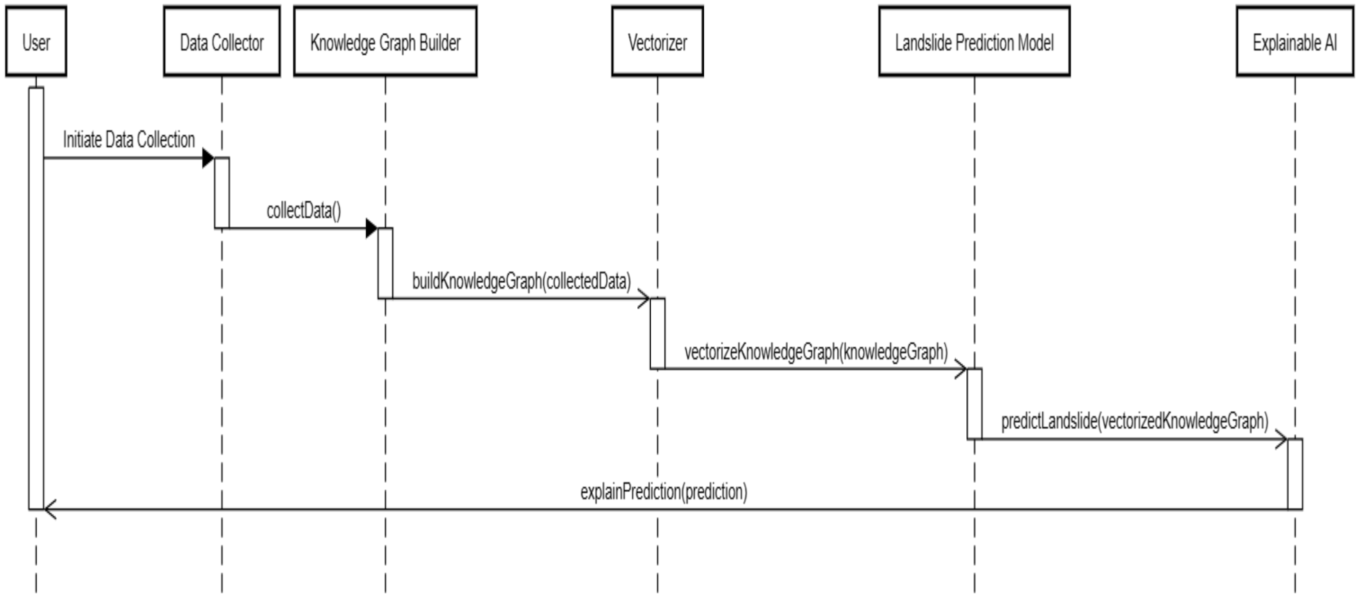


Figure 4.2: Sequence Diagram

4.4 Module Division

4.4.1 Data Acquisition & Pre-processing

Data acquisition involves collecting data from various sources, while data preprocessing entails cleaning, transforming, and formatting the collected data to make it suitable for analysis as given in Figure 4.3. [15]

Data collection: The collection of raw data from various sources such as databases, APIs, files, or sensors encompasses the identification of data sources, extraction of data, and validation to ensure accuracy. This initial step lays the foundation for the subsequent stages of the data processing pipeline.

Data Cleaning: Data cleaning focuses on identifying and rectifying errors or inconsistencies in the raw data. Steps include handling missing values, removing duplicates, correcting errors, and standardizing formats. By addressing these issues, data cleaning ensures that the dataset is reliable and ready for further analysis.

Data Transformation: Data transformation involves the conversion of raw data into a format better suited for analysis. This involves feature engineering, normalization/scaling, encoding categorical variables, and aggregation. These transformations enhance the dataset, making it more conducive to extracting meaningful insights and patterns.

Data Reduction: Data reduction aims to decrease the volume of data while maintaining its analytical value. Techniques like sampling, dimensionality reduction (e.g., PCA), and data summarization are employed. This step is crucial for managing computational resources and simplifying the dataset without compromising the quality of analytical results. Collectively, these stages form a comprehensive approach to preparing data for effective analysis and interpretation.

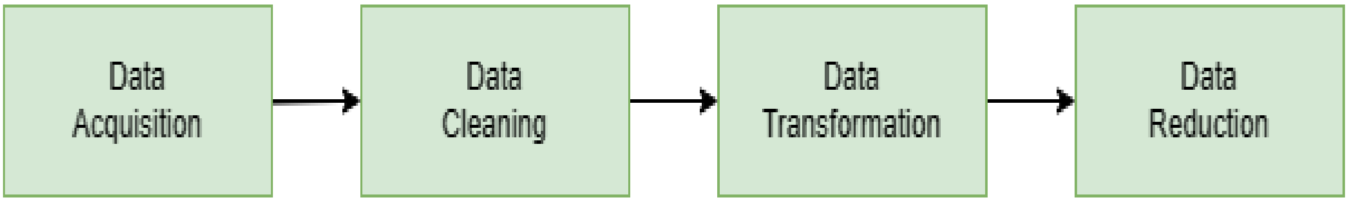


Figure 4.3: Data acquisition and preprocessing

4.4.2 Knowledge Graph Construction

Constructing a knowledge graph involves organizing information in a structured way to represent relationships between entities. Figure 4.4 shows the architecture of knowledge graph.

Identify Relationships: Determine the relationships between entities. Specify the type of relationships and their directionality.

Entity Recognition and Disambiguation: Identify and disambiguate entities within the data. Ensure that different references to the same entity are linked.

Relationship Extraction: Extract information about relationships between entities from the text or data. Use natural language processing (NLP) techniques to understand and extract semantic relationships.

Graph Representation: Represent the entities and relationships in a graph structure. Nodes in the graph represent entities, and edges represent relationships.

Triple Creation: Form triples (subject-predicate-object) to capture the relationships between entities. Each triple consists of a subject, a predicate (relationship), and an object.

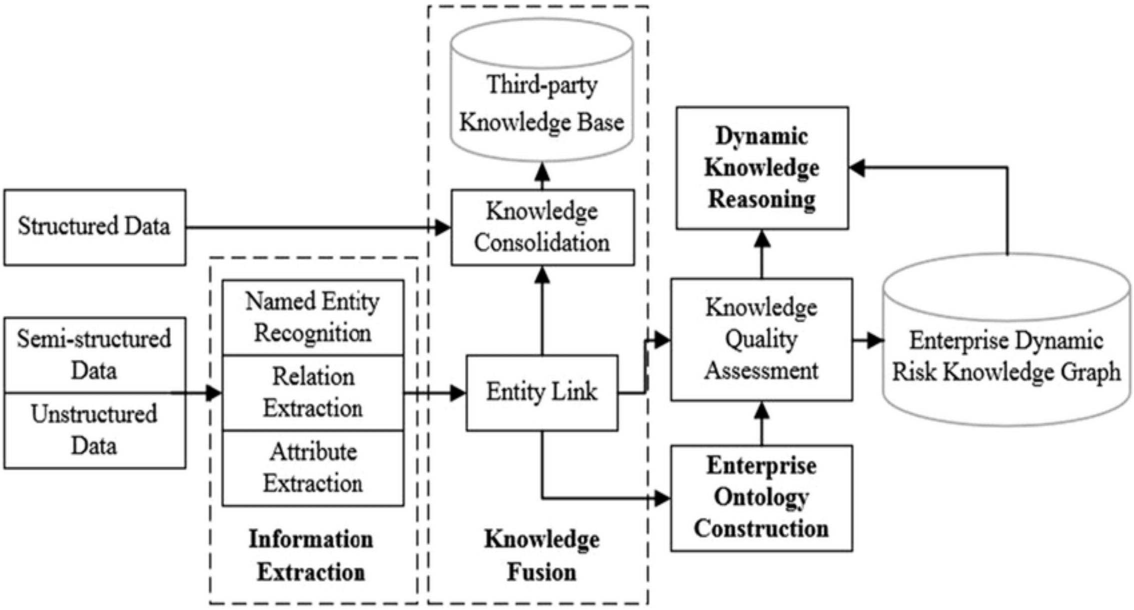


Figure 4.4: Architecture of Knowledge Graph

4.4.3 Explainable AI

Explainable AI (XAI) refers to the concept of designing and developing artificial intelligence systems and algorithms in such a way that their decisions and behaviors can be easily understood and interpreted by humans. The goal of XAI is to make AI models and their decisions transparent, interpretable, and accountable, especially in critical domains where trust, fairness, and safety are paramount.XAI integrates tools and frameworks to assist the comprehension and interpretation of predictions provided by the machine learning models as shown in Figure 4.5.

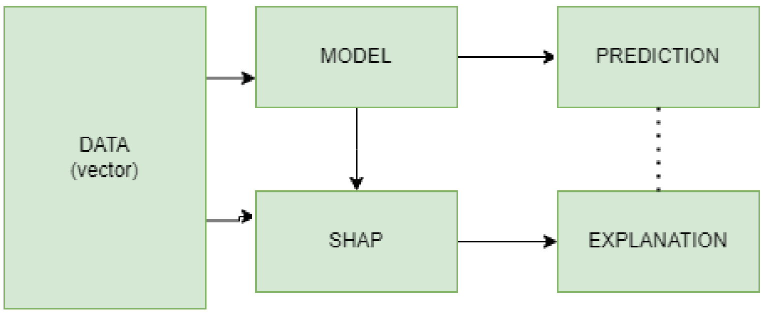


Figure 4.5: Explainable AI

Explainable AI module entails the following features:

Model Transparency: The XAI module could involve using machine learning models that inherently provide transparency, such as decision trees or linear models. These models

are easier to interpret compared to more complex models like neural networks.
Feature Importance: The module may include methods to highlight the importance of different features or variables in the model's decision-making process. For predicting landslides, factors like rainfall, soil type, topography, and vegetation cover might be crucial. Techniques like SHAP values or feature importance plots can be employed.
Local Interpretability: XAI often involves providing explanations for individual predictions, allowing users to understand why the model made a specific decision for a particular instance. This can be crucial in understanding the specific factors contributing to the prediction of a landslide event at a particular location.
Visual Explanations: Visualization tools may be part of the XAI module to represent the model's decision boundaries, relationships between variables, or the impact of different features on predictions. Graphs, charts, and maps could be used to present this information in a comprehensible manner.
User-Friendly Explanations: The XAI module might include natural language explanations or summaries that convey the key factors influencing the model's predictions in a way that is understandable to non-experts.
Interactive Interfaces: Providing an interactive interface could be part of the XAI module, allowing users to explore and manipulate different variables to observe how changes affect the model's predictions. This facilitates a more engaging and user-friendly experience.
Model Validation and Uncertainty: The module includes measures to communicate the uncertainty associated with predictions. Understanding the model's confidence levels can be essential in decision-making processes.
In the context of landslide prediction, the Explainable AI module ensures that the factors leading to a model's prediction are transparent, comprehensible, and aligned with the domain knowledge. This transparency is crucial, especially in applications where decisions based on AI predictions have significant real-world consequences, such as in disaster risk management.

SHAP (SHapley Additive exPlanations):

SHAP values, grounded in cooperative game theory, seek to fairly distribute the "payout" of a predictive model across its features. These values measure the impact of each feature on the deviation between the model's prediction and the average prediction.

In its operation, SHAP takes into account all potential combinations of features and computes the average contribution of each feature across these models. Consequently, SHAP values offer a comprehensive understanding of feature importance and their impact on model predictions.

In practical terms, SHAP values are used in understanding the importance of individual features on a broader scale, illustrating the extent to which each feature influences the model's predictions across the entirety of the dataset. The SHAP framework is depicted in Figure 4.6.

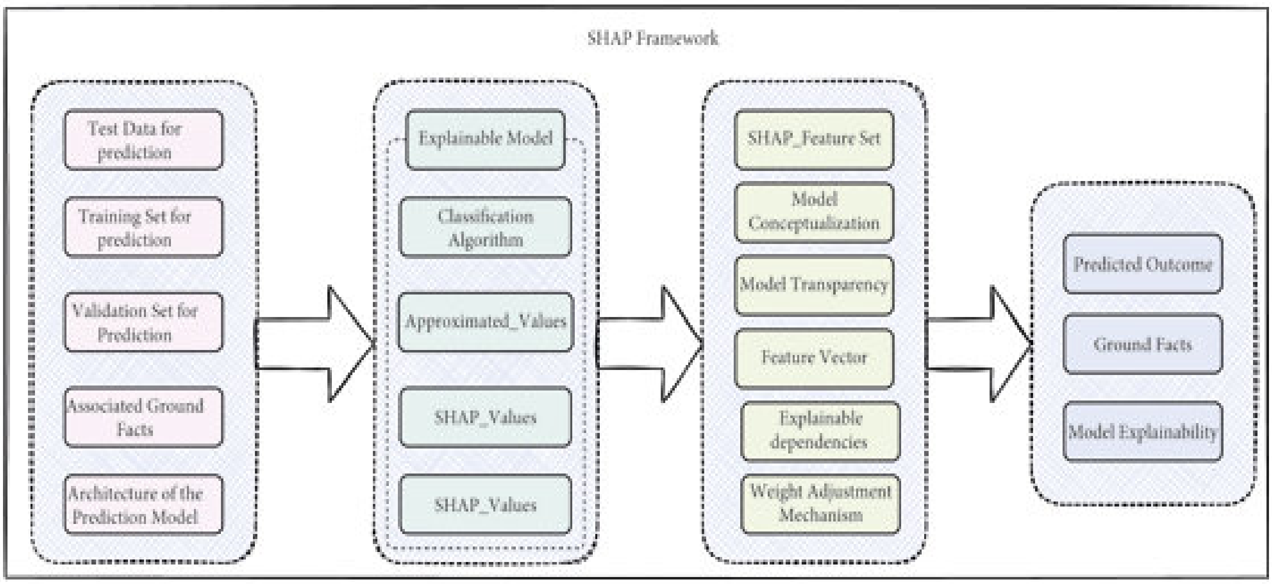


Figure 4.6: SHAP Framework

LIME (Local Interpretable Model-agnostic Explanations):

LIME takes a different approach, focusing on constructing interpretable models that approximate the behavior of complex black-box models within a local region around a specific data point. By perturbing the input data and observing changes in predictions, LIME seeks to understand the local behavior of the model. Figure 4.7 shows the LIME framework.

The operational aspect involves generating perturbed samples around a particular instance of interest and fitting an interpretable model, such as a linear model, to explain the predictions within that local region. LIME proves particularly useful for explaining individual predictions in complex models, facilitating human understanding of why a specific decision was made for a given input.

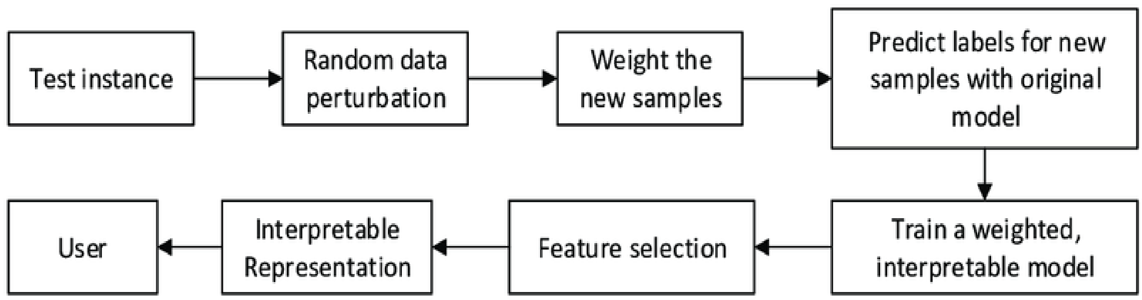


Figure 4.7: Lime Framework

Choosing Between SHAP and LIME:

The decision between SHAP and LIME often hinges on the interpretability needs of a given application. SHAP is apt for understanding the global behavior of a model across the entire dataset, while LIME excels in local interpretability, explaining individual predictions in isolation.

Considerations of complexity also come into play. SHAP offers a comprehensive and theoretically grounded framework, albeit with potential computational intensity. On the other hand, LIME provides a simpler and computationally efficient approach, especially suitable for explaining individual instances.

In practice, we may leverage both SHAP and LIME in conjunction to gain a more holistic and nuanced understanding of a model's behavior.

4.5 Work Breakdown & Responsibilities

Figure 4.8 shows the work breakdown and responsibilities.

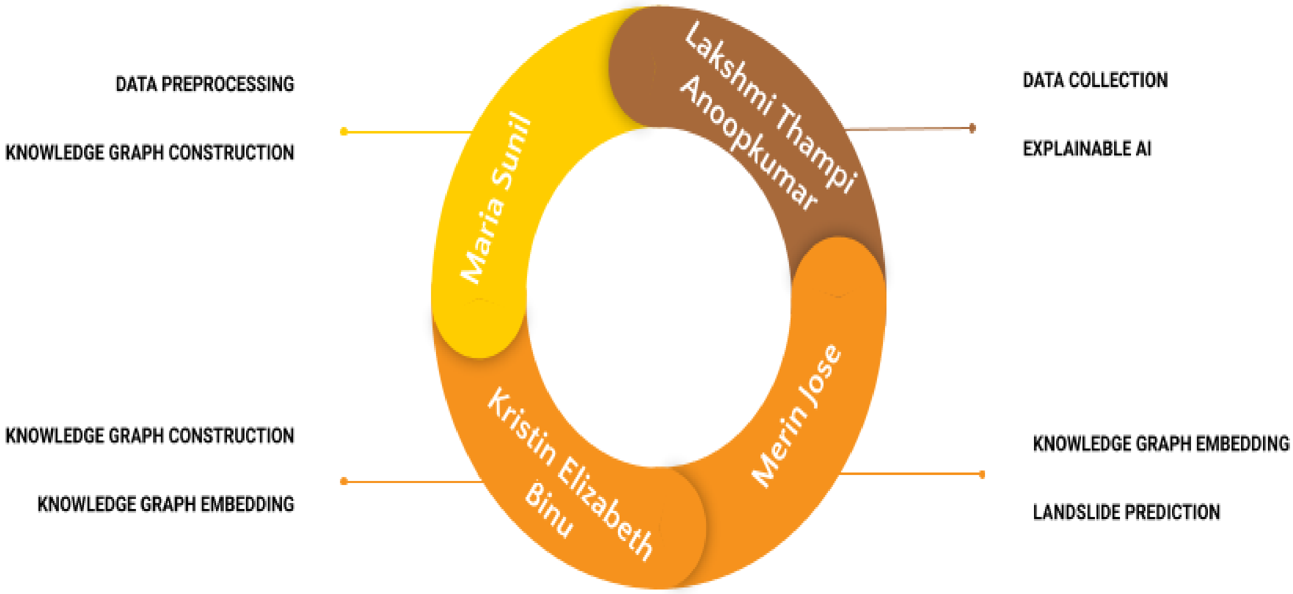


Figure 4.8: Work Breakdown Diagram

4.6 Work Schedule - Gantt Chart

Figure 4.9 shows the Gantt Chart of the work schedule.

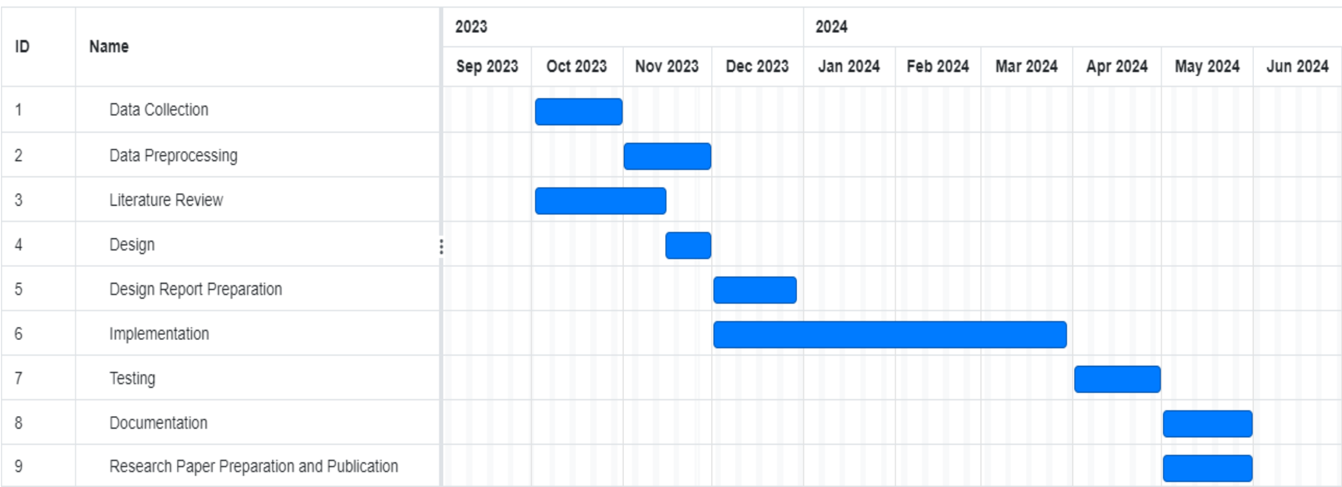


Figure 4.9: Gantt Chart

Chapter 5

Results and Discussions

A model that combines temporal elements (such as seasonal variations and recent weather events) with geographical data (such as slope, curvature, and rainfall) is developed using a spatio-temporal knowledge graph and explainable AI. This model employs Random Forests, enhanced with SHAP and LIME values for explainability, allowing for the visualization of feature impact on prediction outcomes. The result is a robust tool that not only predicts landslide risks with high accuracy but also provides insights into the contributing factors behind each prediction.

5.1 Discussion

A knowledge graph constructed for landslide prediction integrates diverse data types such as geological features, geographical characteristics, meteorological conditions, and temporal events into a unified framework. This graph captures intricate relationships between nodes representing different entities, like soil types, rainfall, seismic activity, and historical landslide incidents. By embedding both spatial and temporal dimensions, the graph offers a dynamic and comprehensive view of potential landslide triggers. Such a structured data model is pivotal for deploying machine learning algorithms, notably in scenarios involving explainable AI, where tools like SHAP help in elucidating the decision-making process. This approach enhances predictive accuracy and provides actionable insights, enabling timely interventions and effective disaster risk management strategies.

Entities such as soil types and rainfall rates are identified and linked in a graph, enabling the prediction models to analyze relationships and triggers, thus enhancing the accuracy of landslide forecasts. Figure 5.1 shows the knowledge graph constructed from unstructured data.

Constructing a knowledge graph from structured data involves defining a schema layer,

Figure 5.1: Knowledge graph constructed from Unstructured Data

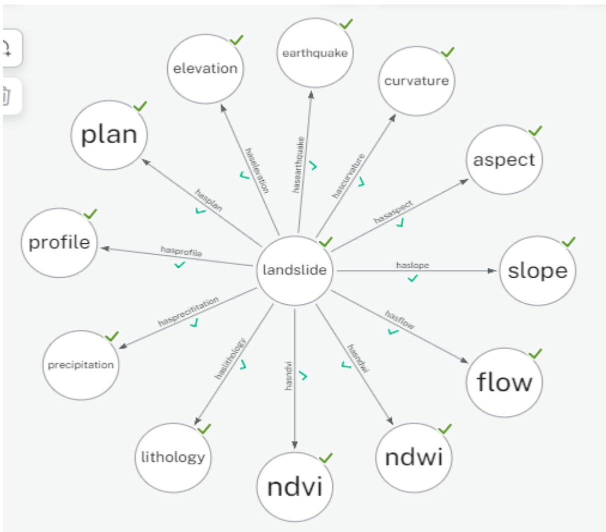


Figure 5.2: Schema layer of the Knowledge Graph of Structured data

which serves as a structural blueprint outlining key elements such as entity types, relationship types, and their attributes. In Figure 5.2, the schema includes entities like "Precipitation," and "Landslide," with relationships such as "hasslope". Attributes could detail specific properties like the degree of slope or rainfall intensity. This schema ensures that the graph is systematically organized, with clear definitions for how different types of data are related and stored, facilitating precise queries and analysis. This structured approach not only enhances data interoperability and querying efficiency but also supports advanced analytics for predictive modeling.

Figure 5.3 shows the instance layer of a knowledge graph for landslide prediction using

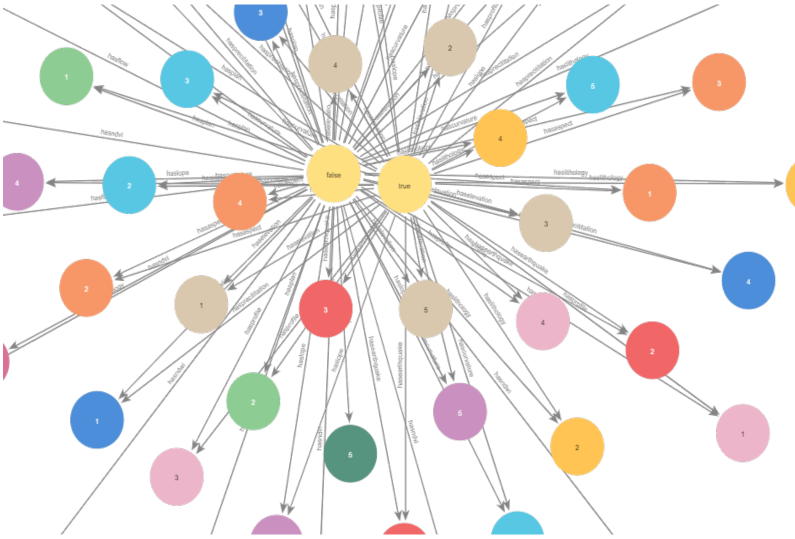


Figure 5.3: Knowledge graph constructed from Structured Data

structured data refers to the actual data that populates the schema previously defined. This layer consists of specific instances or records that conform to the structure set out by the schema, including detailed information on various entities and their relationships. The results of the proposed model and how well the Random Forest model may be interpreted to produce accurate landslide forecasts are examined. Both the SHAP and LIME models use the full training dataset to offer both global and local explanations. Figures 5.4 & 5.5 illustrate the interpretation of the positive and negative cases of a landslide event using the LIME model.

The rightmost value denotes the prediction given by the LIME prediction model for the given test vector. In Figure 5.4, the landslide is predicted with 94% confidence. Because the elevation is equal to 1, profile is greater than 4, precipitation is greater than 4, aspect ratio is greater than 2, curvature is less than 2, NDWI is greater than 2, earthquake is greater than 2 and NDVI is greater than 2, the model predicted this event to be a landslide event. Figure 5.5 gives the interpretation of a non-landslide event with 83% confidence. Since the precipitation is less than 3, NDVI is greater than 4, elevation is greater than 2, profile is less than 2, earthquake is less than 2, aspect and curvature.

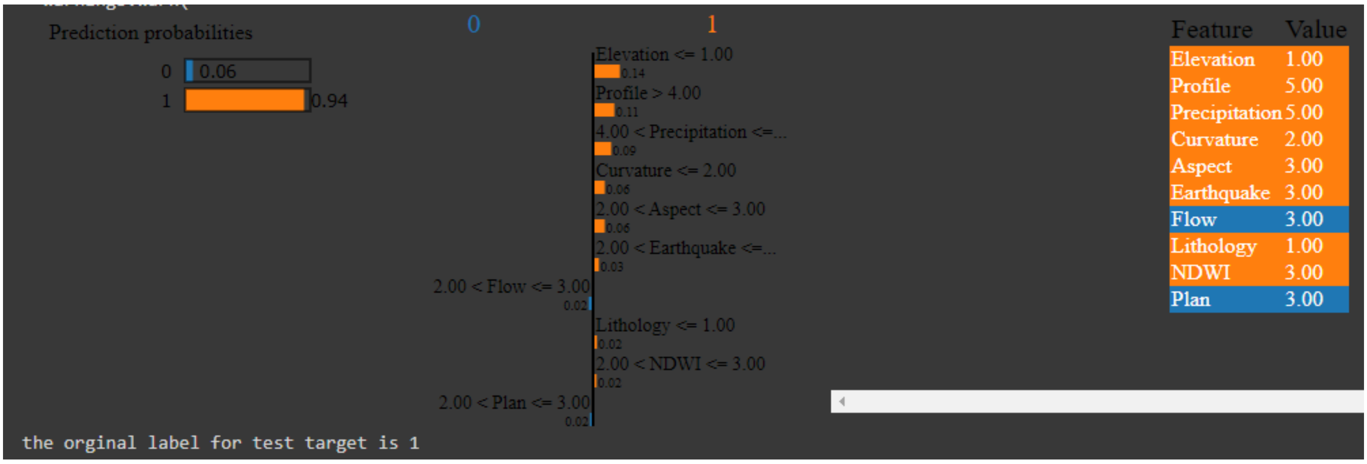


Figure 5.4: Prediction of Landslide Event using LIME Model

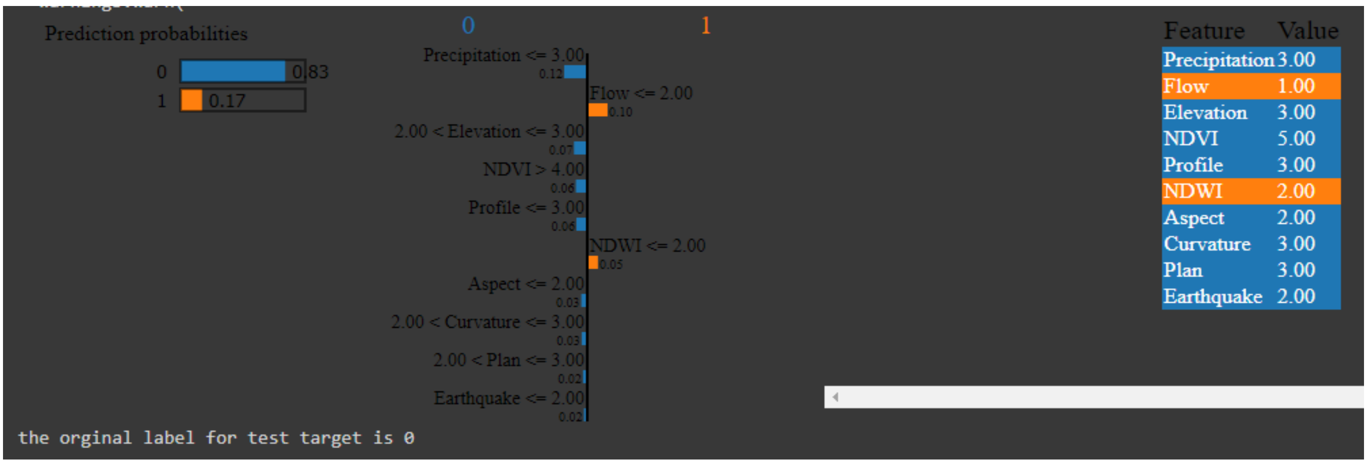


Figure 5.5: Prediction of non Landslide Event using LIME Model

Figure 5.6 represents a bar graph showing the relative importance of features in the landslide prediction model using SHAP. The features are marked on the Y-axis, and their relative importance is marked on the X-axis. The longer the bar, the greater will be the precedence of the corresponding feature for predicting landslides.

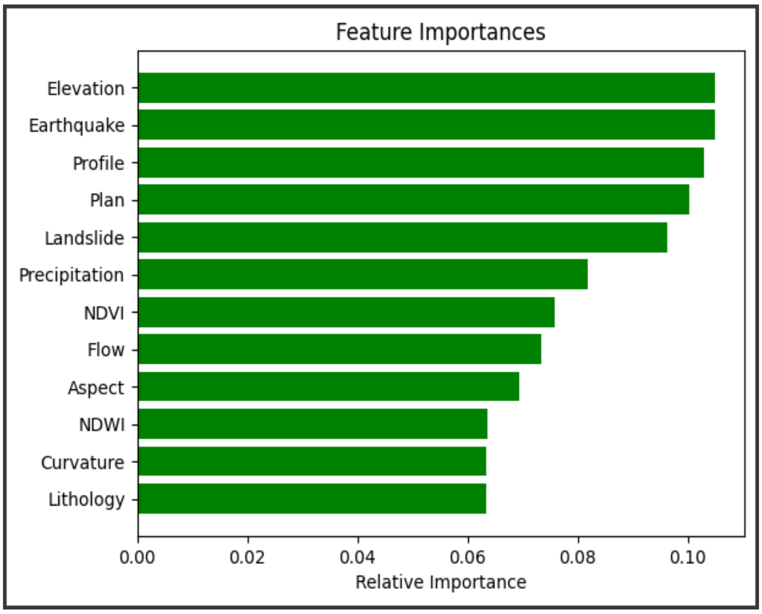


Figure 5.6: Feature Importance of landslide causing factors

Figure 5.7 shows the summary plot of SHAP analysis for a non-landslide event. The average impact on the model's output magnitude of each feature is shown in the plot. The features are listed on the Y-axis, and their corresponding magnitude of impact is shown on the X-axis. The red bar indicates a positive influence on the result, and a negative influence is indicated by the blue bar. The longer the red part of the bar (and the shorter the blue part of the bar), the greater the influence of the feature on the model's output and vice versa. The plot shows that the "Flow" feature has the largest positive influence on the model's output. In contrast, the "Lithology" feature has the largest negative impact, i.e., on average, higher flow values tend to increase the model's prediction of a landslide. In comparison, higher lithology values tend to decrease the odds of a positive landslide event.

Sorted by relevance, Figure 5.8 displays the dispersal of SHAP values for every feature. The SHAP values are plotted on the X-axis against the features on the Y-axis. Each point corresponds to an instance from the dataset. The color of the point indicates the magnitude of the influence of a certain attribute. Red indicates the attribute to be associated with a large value while blue indicates association with a small value. Higher values (red dots) in the positive direction indicate a larger contribution as is the case for the feature precipitation, slope, and profile. They strongly influence the likelihood of a

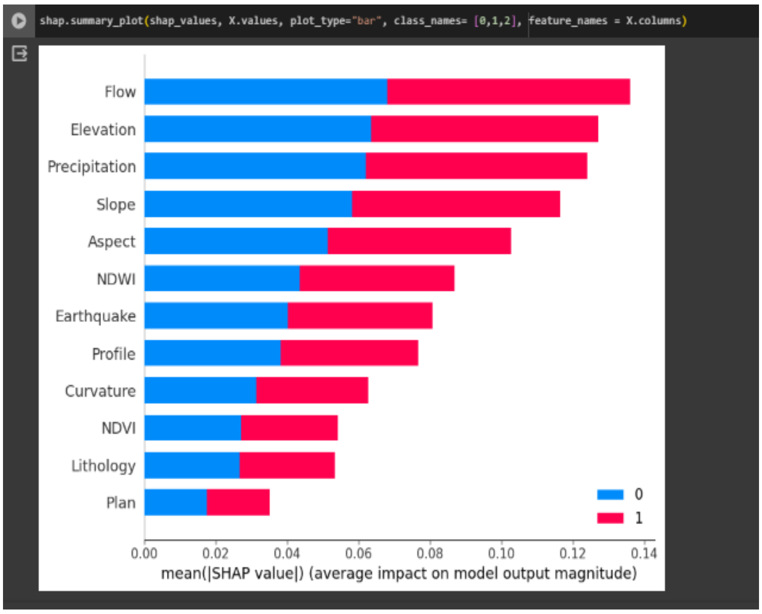


Figure 5.7: Mean SHAP values of each attribute

landslide. SHAP dependence plots in Figure 5.9 illustrate how a given feature affects the

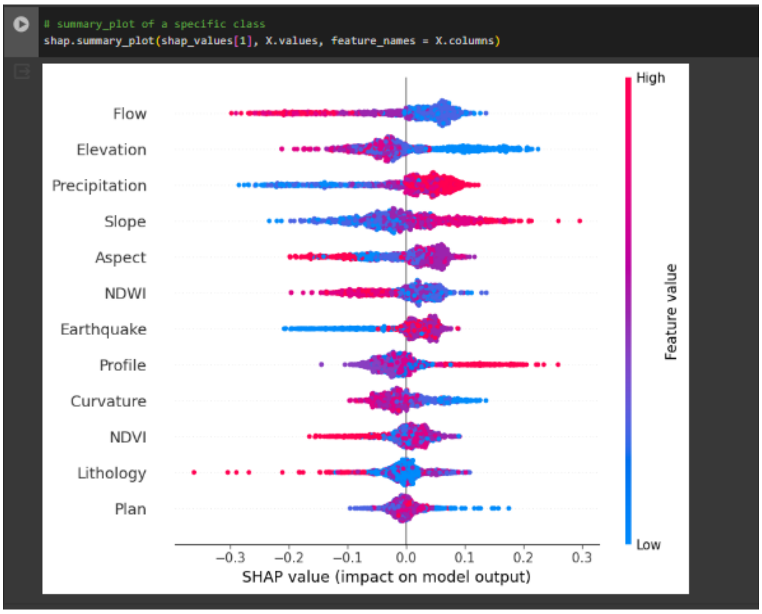


Figure 5.8: Distribution of SHAP values for each feature

entire dataset. The aspect values are plotted on the X-axis against the aspect's SHAP value on the Y-axis for several samples are shown in the figure. Interaction effects drive the vertical dispersion of SHAP values at a single feature value, and a different feature is selected for coloring to emphasize potential interactions. The variance is also displayed on the Y-axis in SHAP dependency.

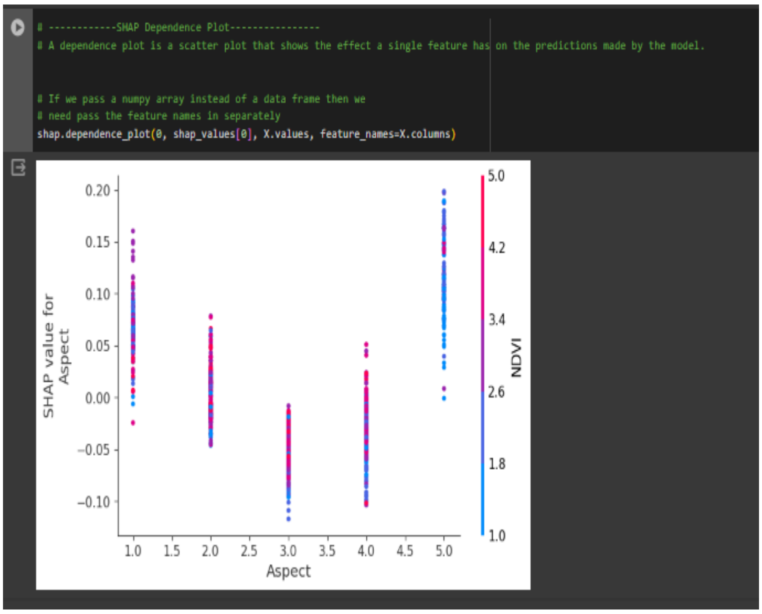


Figure 5.9: Dependence plot for the entire dataset

The local interpretation of a landslide incident is depicted in Figure 5.10. A positive influence on the result is indicated by the red bar, and a negative influence is indicated by the blue bar. The lithology feature has a 0.36 influence on how a landslide turns out. In the upper-right corner, the likelihood value of a landslide occurring, or the positive case, is represented by f(x)=0.91 in the machine learning model. The expected value (EV) is shown at the bottom of the figure, E[f(x)]=0.484. The actual percentage of positive cases from the training dataset that was used to develop the ML model is called the EV, which is also referred to as the background data in the SHAP technique. The EV can be viewed as a beginning point because it represents a crudely expected outcome. The result can be obtained by summing the SHAP values of each feature and EV. Stated differently, the SHAP values can show the relative contributions of each feature to the result when EV is used as the beginning point and Z(x) is used as the terminus.

5.2 Conclusion

In conclusion Knowledge graph was constructed using unstructured and structured data to model and manage complex interactions among various environmental, geological, and climatic factors and to derive insights from the same.The application of machine learning techniques, specifically Random Forest algorithms, enabled the predictive modeling of

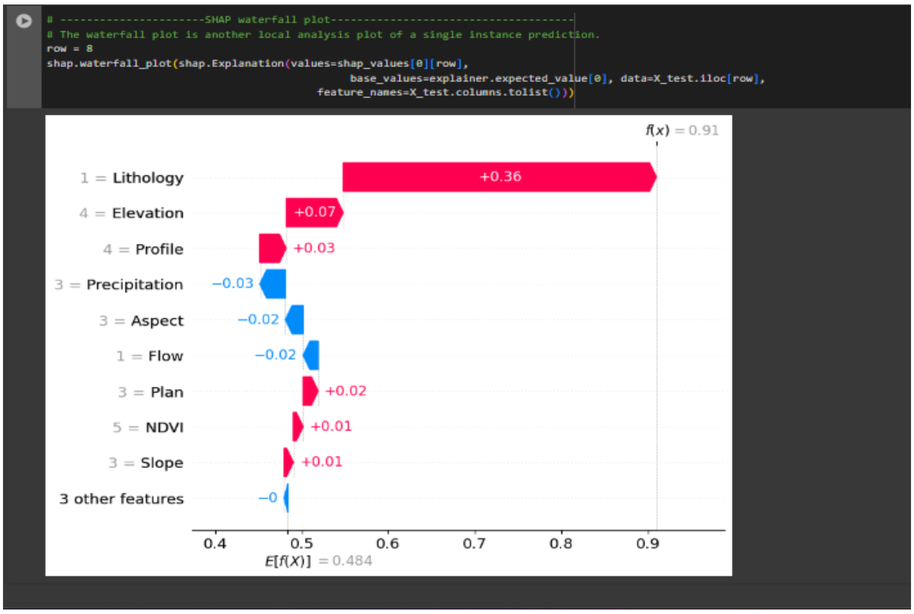


Figure 5.10: Local Interpretation of Landslide incident

landslide occurrences with high accuracy. Crucially, the incorporation of explainable AI tools like SHAP values and LIME provided clear insights into the decision-making process of the model, highlighting key factors like rainfall intensity and soil stability that influence landslide likelihood.

Chapter 6

Conclusions & Future Scope

In conclusion, the integration of Explainable AI (XAI) and Spatio-Temporal Knowledge Graphs in the domain of Landslide Prediction represents a significant stride toward more accurate, interpretable, and actionable forecasting systems. By leveraging XAI techniques, the model's decision-making processes have been made transparent, providing stakeholders and decision-makers with insights into the factors influencing landslide predictions. The use of Spatio-Temporal Knowledge Graphs enhances the model's contextual awareness, capturing the dynamic relationships between geographical and temporal variables that contribute to landslide events.

The interpretability afforded by XAI is paramount in building trust and facilitating informed decision-making. Stakeholders can now understand the pivotal features driving predictions, enabling better risk assessment and proactive mitigation strategies. This transparency is especially crucial in domains where the consequences of inaccurate predictions, such as landslides.

The domain of Landslide Prediction using XAI and Spatio-Temporal Knowledge Graphs offers a rich terrain for further exploration and advancement. One avenue for future research involves the exploration of more sophisticated machine learning models within the XAI framework, aiming to enhance prediction accuracy without sacrificing interpretability. Another promising direction is the development of methods to dynamically update Spatio-Temporal Knowledge Graphs, allowing models to adapt to real-time data and evolving environmental conditions for increased responsiveness. Consideration of ensemble approaches, combining predictions from multiple algorithms while leveraging XAI, could further improve model robustness. Building interactive interfaces that involve stakeholders in refining the model and exploring possibilities for cross-domain collaboration between geoscientists, machine learning experts, and policymakers are vital steps toward creating more effective, inclusive, and ethically sound systems. Additionally, the integration of AI predictions into existing early warning systems and a comprehensive examination of ethical implications will contribute to the responsible deployment of these technologies in critical domains such as disaster prediction. This forward-looking agenda aims to propel the field, ensuring that the synergy between XAI and Spatio-Temporal Knowledge Graphs continues to yield impactful insights for mitigating the impact of landslides on communities and infrastructure.

Chapter 7

Paper Published/Accepted

Dynamic Landslide Prediction, Monitoring, and Early Warning with Explainable AI: A Comprehensive Approach, accepted and recommended for publication at the 3rd International Conference on Applied Artificial Intelligence and Computing - ICAAIC 2024, organized by R P Sarathy Institute of Technology, Salem, Tamil Nadu, India on June 05th, 2024, published by IEEE.

References

[1] L. Chen, X. Ge, L. Yang, W. Li, and L. Peng, "An improved multi-source data-driven landslide prediction method based on spatio-temporal knowledge graph," *Remote Sensing*, vol. 15, no. 8, 2023.

[2] X. Ma, "Knowledge graph construction and application in geosciences: A review," *Computers & Geosciences*, vol. 161, p. 105082, 2022.

[3] X. Ge, Y. Yang, J. Chen, W. Li, Z. Huang, W. Zhang, and L. Peng, "Disaster prediction knowledge graph based on multi-source spatio-temporal information," *Remote Sensing*, vol. 14, no. 5, 2022.

[4] B. Xu, C. Zhang, W. Liu, J. Huang, Y. Su, Y. Yang, W. Jiang, and W. Sun, "Landslide identification method based on the fkgrnet model for remote sensing images," *Remote Sensing*, vol. 15, no. 13, p. 3407, 2023.

[5] E. Collini, L. I. Palesi, P. Nesi, G. Pantaleo, N. Nocentini, and A. Rosi, "Predicting and understanding landslide events with explainable ai," *IEEE Access*, vol. 10, pp. 31 175–31 189, 2022.

[6] B. T. Pham, I. Prakash, J. Dou, S. K. Singh, P. T. Trinh, H. T. Tran, T. M. Le, T. Van Phong, D. K. Khoi, A. Shirzadi *et al.*, "A novel hybrid approach of landslide susceptibility modelling using rotation forest ensemble and different base classifiers," *Geocarto International*, vol. 35, no. 12, pp. 1267–1292, 2020.

[7] X. Ge, Y. Yang, L. Peng, L. Chen, W. Li, W. Zhang, and J. Chen, "Spatio-temporal knowledge graph based forest fire prediction with multi source heterogeneous data," *Remote Sensing*, vol. 14, no. 14, p. 3496, 2022.

[8] X. Hao, Z. Ji, X. Li, L. Yin, L. Liu, M. Sun, Q. Liu, and R. Yang, "Construction and application of a knowledge graph," *Remote Sensing*, vol. 13, no. 13, p. 2511, 2021.

[9] D.-Y. Chen, L. Peng, W.-C. Li, and Y.-D. Wang, "Building extraction and number statistics in wui areas based on unet structure and ensemble learning," *Remote Sensing*, vol. 13, no. 6, 2021. [Online]. Available: https://www.mdpi.com/2072-4292/13/6/1172

[10] F. Lehmann, "Semantic networks," *Computers Mathematics with Applications*, vol. 23, no. 2, pp. 1–50, 1992. [Online]. Available: https://www.sciencedirect.com/science/article/pii/0898122192901355

[11] J. Corominas, R. copons llorens, J. Moya, J. Vilaplana, J. Altimir, and J. Amigó, "Quantitative assessment of the residual risk in a rockfall protected area," *Landslides*, vol. 2, pp. 343–357, 12 2005.

[12] D. Zhiqiang, L. Yu, Z. Yeting, T. Yuqi, and Z. Wenhao, "Knowledge graph construction method on natural disaster emergency," *Geomatics and Information Science of Wuhan University*, vol. 45, no. 9, pp. 1344–1355, 2020.

[13] S. L. Ullo, A. Mohan, A. Sebastianelli, S. E. Ahamed, B. Kumar, R. Dwivedi, and G. R. Sinha, "A new mask r-cnn-based method for improved landslide detection," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 3799–3810, 2021.

[14] T. Ebisu and R. Ichise, "Generalized translation-based embedding of knowledge graph," *IEEE Transactions on Knowledge and Data Engineering*, vol. 32, no. 5, pp. 941–951, 2019.

[15] B. Aslam, A. Zafar, and U. Khalil, "Development of integrated deep learning and machine learning algorithm for the assessment of landslide hazard potential," *Soft Computing*, vol. 25, no. 21, pp. 13 493–13 512, 2021.

Appendix A: Final Presentation

Phase II - Interim Evaluation II

Landslide Prediction using XAI and Spatio-Temporal Knowledge Graph

U2003123 - Lakshmi Thampi Anoopkumar

U2003122 - Kristin Elizabeth Binu

U2003128 - Maria Sunil

U2003133 - Merin Jose

RSET

May 1, 2024

Guide: Dr. Preetha K. G.

Contents

Problem definition

The project aims to develop a Landslide Prediction system utilizing spatio-temporal knowledge graphs and Explainable AI to enhance our understanding of landslide dynamics, provide accurate predictions, and offer interpretable insights into the factors contributing to landslide occurrences.

Purpose and Need

Purpose

- Early Warning and Risk Reduction
- Precise Prediction
- XAI for Transparency
- Resource Allocation
- Infrastructure Planning and Development
- Public Awareness

Need

The use of XAI and Spatio-Temporal Knowledge Graphs in landslide prediction is essential for improving accuracy, transparency and the overall effectiveness of mitigation and preparedness efforts, ultimately saving lives and resources in the face of this natural hazard.

Project Objectives

- Minimizing risk and damage by providing early warnings
- Understanding triggering factors
- Developing effective mitigation strategies, and safeguarding vulnerable communities and infrastructure.

Literature Survey I

S.NO.	PAPER	METHOD
1	An Improved Multi-Source Data-Driven Landslide Prediction Method Based on Spatio-Temporal Knowledge Graph.	Spatio-temporal knowledge graph and machine learning models
2	Disaster Prediction Knowledge Graph Based on Multi- Source Spatio-Temporal Information.	Disaster prediction knowledge graph
3	Multi-source Knowledge Embedding Research of Knowledge Graph	Represents knowledge graph entities as continuous vector embeddings in a continuous vector space

Literature Survey II

S.NO.	PAPER	METHOD
4	An explainable AI (XAI) model for landslide susceptibility modeling	CNN, SHAP
5	Predicting and Understanding Landslide Events With Explainable AI	XGBoost, SHAP
6	Landslide Identification Method Based on the FKGRNet Model for Remote Sensing Images	Knowledge graphs and ResNet

Literature Survey III

S.NO.	PAPER	METHOD
7	Information extraction and knowledge graph construction from geoscience literature	Uses NLP to extract information from geoscience literature
8	Knowledge graph construction and application in geosciences: A review	KG construction; KG application in data collection, curation, and service; KG application in data analysis; Challenges and trends of geoscience KG creation and application in the near future.

Existing methods

- Conducting field surveys to assess the geological and geomorphological characteristics of an area.
- Monitoring and analyzing rainfall patterns as heavy rainfall is a significant trigger for landslides.
- Employing radar technology to measure ground deformations and identify areas susceptible to landslides.
- Using GNSS technology to monitor ground movement and detect potential landslide-prone areas.

Proposed Method

A method for landslide prediction that combines Explainable Artificial Intelligence (XAI) and Spatio-Temporal Knowledge Graphs (STKGs) to enhance landslide prediction and understanding. Our proposed system leverages XAI techniques to create models that not only predict the likelihood of landslides but also provide interpretable explanations for these predictions. By utilizing STKGs, we integrate diverse data sources, including topography, weather patterns, historical landslide events, and land-use changes, into a unified knowledge graph. This STKG enables us to capture complex relationships and temporal patterns that contribute to landslide occurrences. The fusion of XAI and STKGs offers a comprehensive and transparent solution for landslide prediction, enhancing both the accuracy and trustworthiness of predictive models.

Knowledge Graph

- A knowledge graph is a semantic network knowledge base composed of various entities and relationships in the objective world.
- In a knowledge graph, entities are represented as nodes, and the relationships between these entities are represented as edges or links.
- Landslide domain knowledge is extratcted from multisource data such as structured relational remote sensing databases, semi-structured web news, and unstructured monographs and construct a large-scale landslide knowledge graph.

Landslide Knowledge Graph

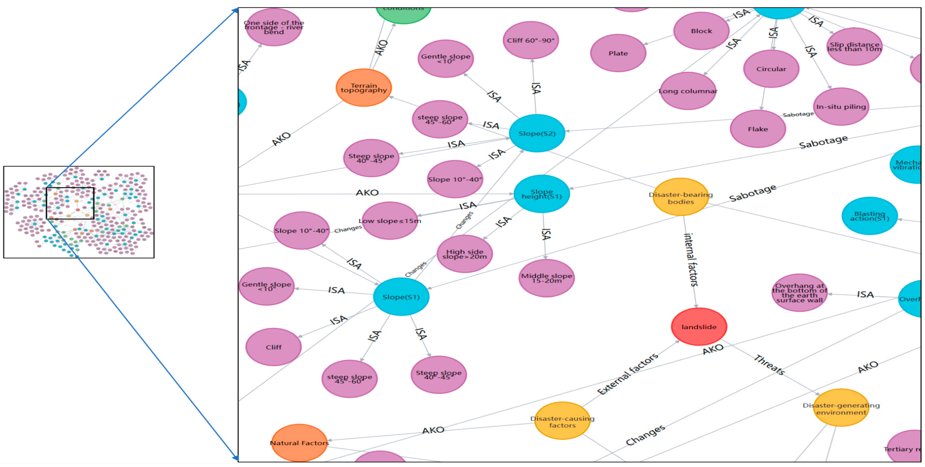


Figure: Example of the schema layer of the landslide knowledge gaph

eXplainable Artificial Intelligence

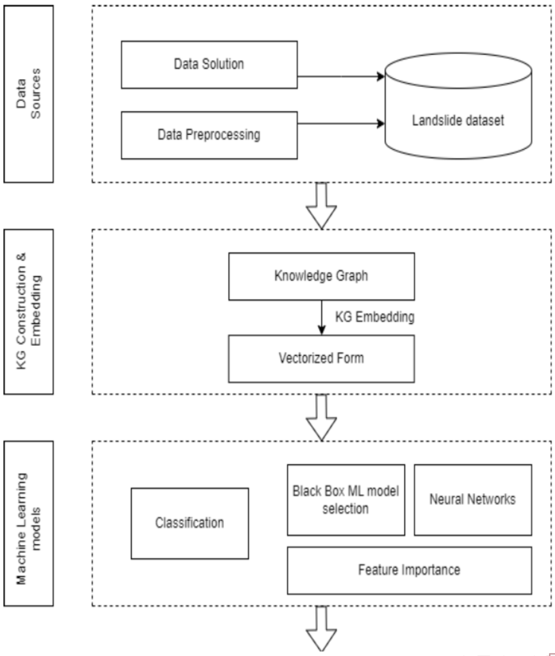
- XAI integrates tools and frameworks to assist the comprehension and interpretation of predictions provided by the machine learning models.
- It helps characterize model accuracy, fairness, transparency and outcomes in AI-powered decision making.
- **Local Interpretable Model-agnostics Explanation (LIME):** It takes decisions and, by querying nearby points, builds an interpretable model that represents the decision, then uses that model to provide explanations.
- **Shapely Additive Explanation (SHAP):** It explains a given prediction by mathematically computing how each feature contributed to the prediction. It functions largely as a visualization tool, and can visualize the output of a machine learning model to make it more understandable.

Phase II - Interim Evaluation II Landslide Prediction using XAI and Spatio-Temporal Knowledge

Novelty Of Idea

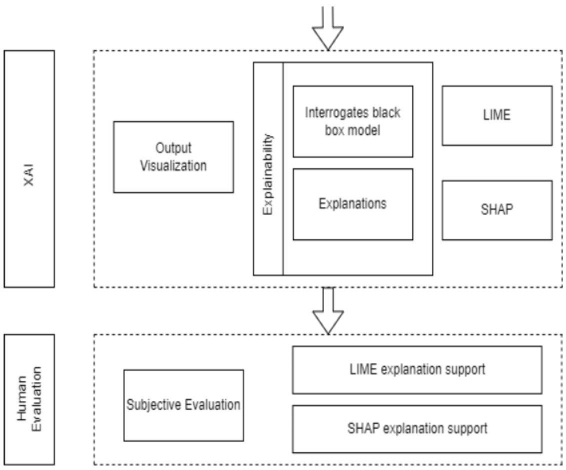
- **Spatio-Temporal Knowledge Graphs:** Representing complex relationships between locations and time periods, aiding analysis of temporal patterns and spatial interactions in data.
- **Explainable AI Techniques:** Ensuring transparent and understandable predictions, enhancing trust by providing insights into prediction reasoning.
- **Unique Integration in Landslide Prediction System:** Integrating spatio-temporal knowledge graphs and Explainable AI techniques for comprehensive analysis of landslide dynamics and interpretable insights into contributing factors, a departure from traditional approaches.
- **Enhanced Understanding and Interpretability:** Leveraging these techniques to provide deeper insights into landslide dynamics, enabling informed decisions and proactive risk mitigation measures by stakeholders.

Scope Of Implementation - Architecture Diagram

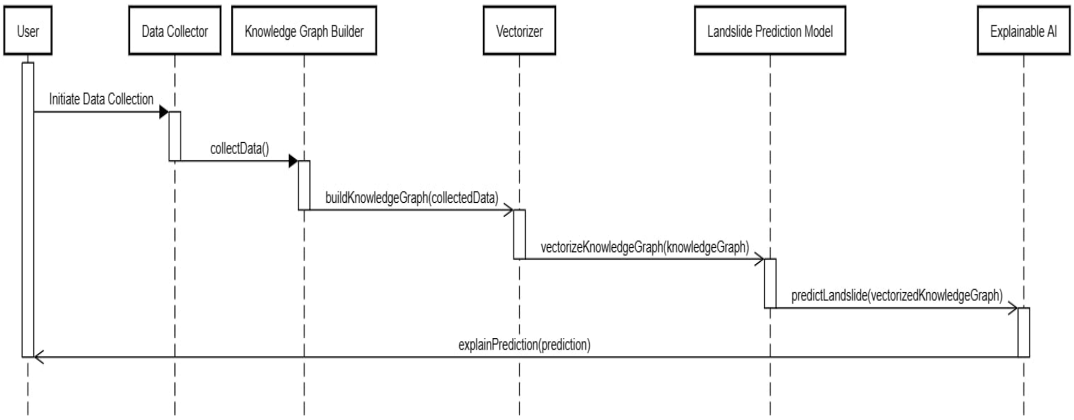


Phase II - Interim Evaluation II Landslide Prediction using XAI and Spatio-Temporal Knowledge

Architecture Diagram

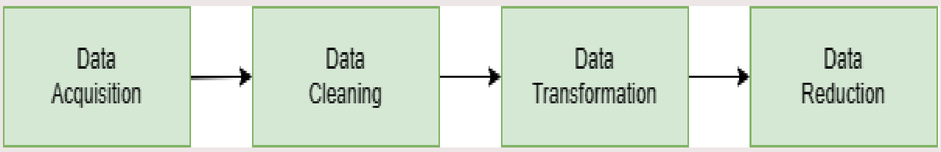


Sequence Diagram



Modules

Data Aquisition & Preprocessing



Modules

Knowledge graph

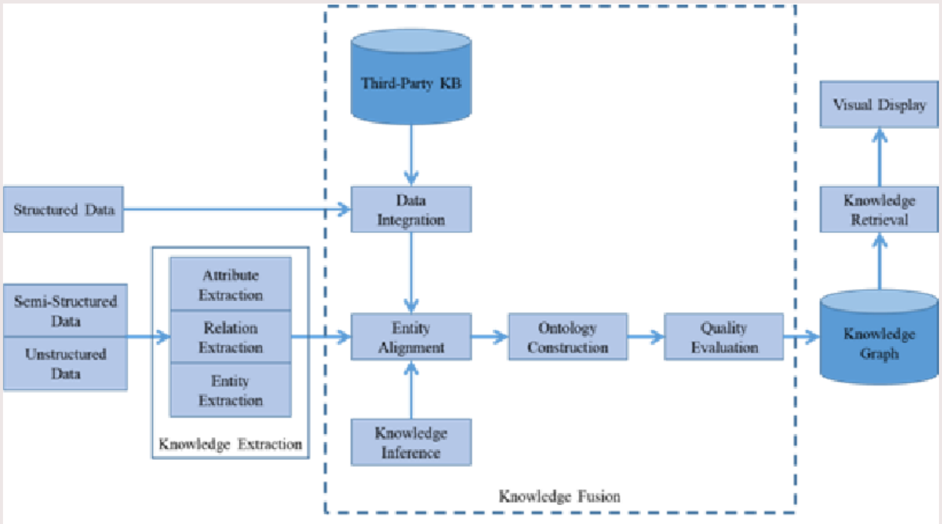
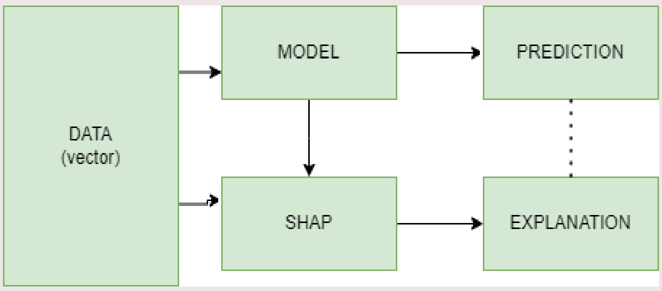


Fig. 1. The Architecture of knowledge Graph

Phase II - Interim Evaluation II Landslide Prediction using XAI and Spatio-Temporal Knowledge

Modules

Prediction and XAI



Dataset Identified

- Landslide Prediction for Muzaffarabad-Pakistan
- Landslides After Rainfall, 2007-2016
- Global Landslide Catalog
- Landslide Images (kaggle)

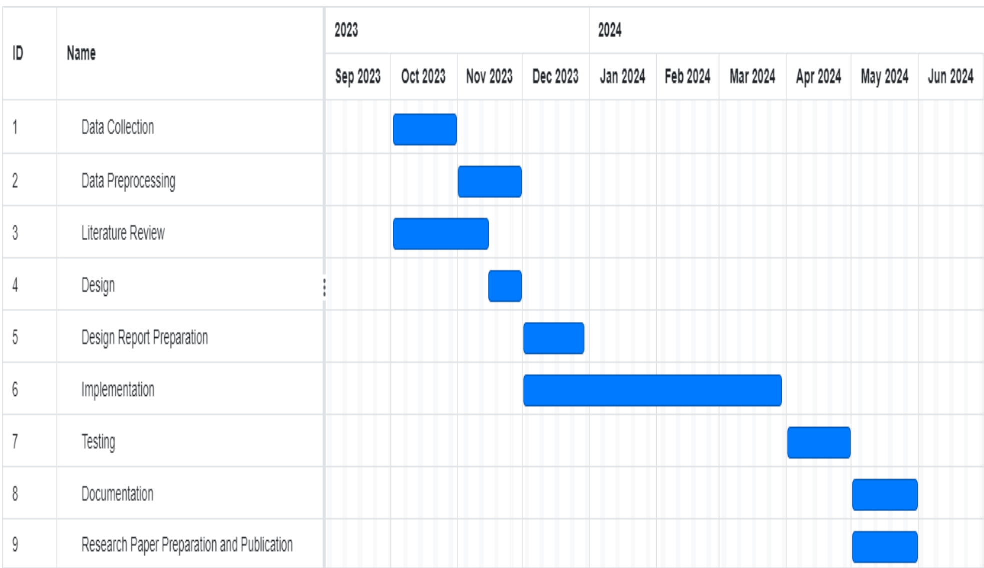
Assumptions

- Data used for model development is accurate, complete, and representative of the study area.
- The underlying geological and environmental conditions are relatively constant over the prediction period.

Hardware & Software Requirements

- System: 16GB RAM, 32 bit CPU
- Programming Languages: Python
- Machine Learning Frameworks: TensorFlow
- Explainable AI (XAI) Libraries: SHAP, LIME
- Geospatial Libraries: GeoPandas
- Integrated Development Environment (IDE): Jupyter Notebooks
- Knowlegde Graph Construction: Neo4j

Gantt Chart



Risks and Challenges

- Unavailability of large datasets for more accurate result.
- Handling and processing of large datasets efficiently requires high end systems.
- Landslide datasets can suffer from data quality issues, such as missing or inconsistent data, incorrect labels, or outdated information.
- Model Complexity
- Model Generalization

Phase II - Interim Evaluation II Landslide Prediction using XAI and Spatio-Temporal Knowledge

Work Done (30% Evaluation)

```
import numpy as np
import pandas as pd
#from sklearn import datasets

# Let's import the data from sklearn
#from sklearn.datasets import load_wine
#wine_db=load_wine()
landslide_db=pd.read_csv('landslide.csv')
#Conver to pandas dataframe
#landslide=pd.DataFrame(data=np.c_[landslide_db['data'],landslide_db['target']],columns=landslide_db['feature_names']+['target'])
print(landslide_db)
```

```
      Landslide  Aspect  Curvature  Earthquake  Elevation  Flow  Lithology  \
0             0       3          3           2          2     2          1
1             0       1          5           2          3     1          1
2             0       3          4           3          2     2          4
3             0       1          3           3          3     5          1
4             0       5          4           2          1     4          1
...         ...     ...        ...         ...        ...   ...        ...
1207          1       4          2           1          4     2          5
1208          1       4          5           1          5     3          5
1209          1       3          4           1          5     2          5
1210          1       2          2           1          3     1          1
1211          1       3          4           1          3     2          1

      NDVI  NDWI  Plan  Precipitation  Profile  Slope
0        4     2     2              3        3      2
```

Work Done (30% Evaluation)

	NDVI	NDWI	Plan	Precipitation	Profile	Slope
0	4	2	2	3	3	2
1	4	2	5	5	2	2
2	3	2	4	5	2	2
3	2	4	3	5	3	3
4	2	4	3	3	1	4
...	...	...	...	...	...	...
1207	1	5	3	2	4	2
1208	1	5	5	2	1	5
1209	2	3	3	2	2	5
1210	5	1	1	1	3	3
1211	4	1	4	1	2	3

[1212 rows x 13 columns]

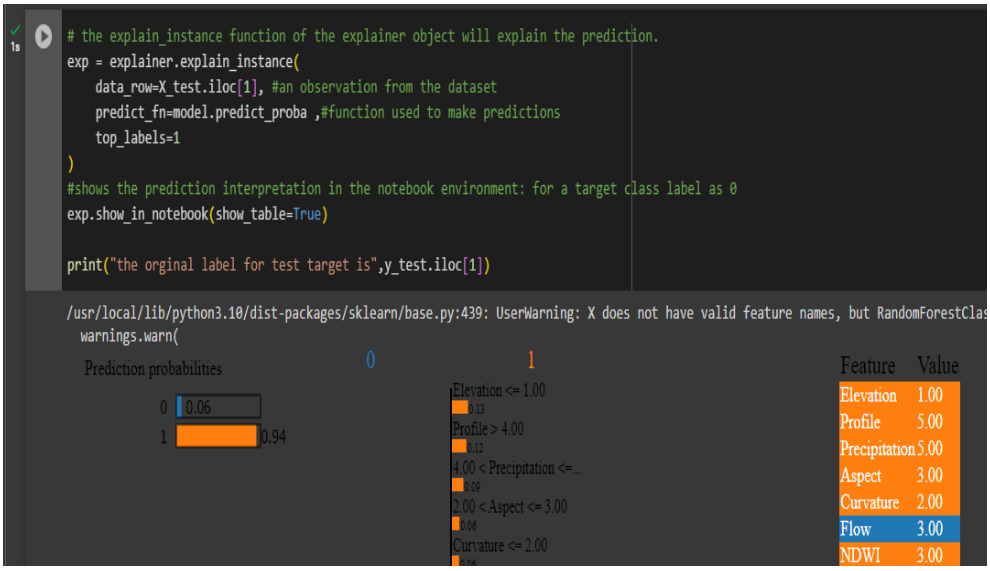
Work Done (30% Evaluation)

```
[3] from sklearn.model_selection import train_test_split

    X = landslide_db.drop('Landslide', axis=1)
    y = landslide_db['Landslide']

    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=0.2, random_state=42
    )
```

```
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
score = model.score(X_test, y_test)
```

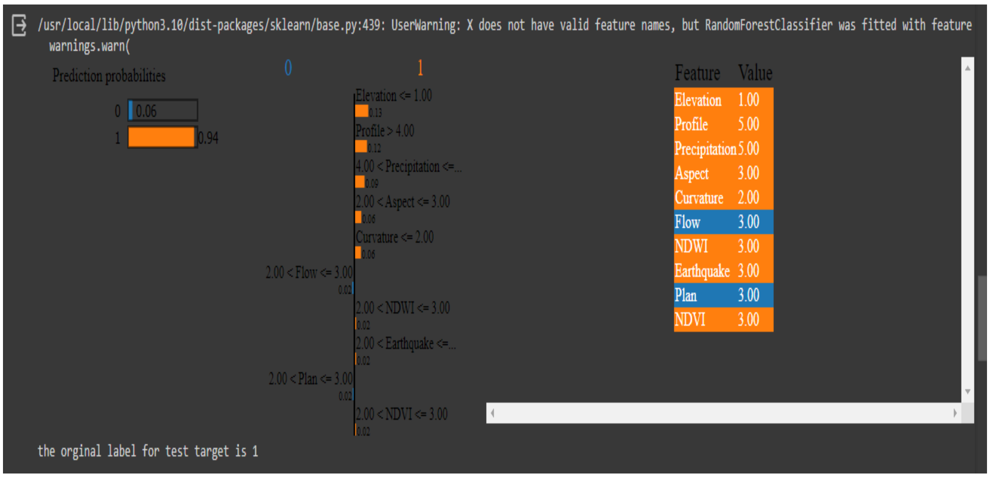
```
import lime
from lime import lime_tabular

explainer = lime_tabular.LimeTabularExplainer(
    training_data=np.array(X_train),
    feature_names=X_train.columns,
    class_names=[0,1],
    mode='classification'
)
```

Work Done (30% Evaluation)



Phase II - Interim Evaluation II Landslide Prediction using XAI and Spatio-Temporal Knowledge

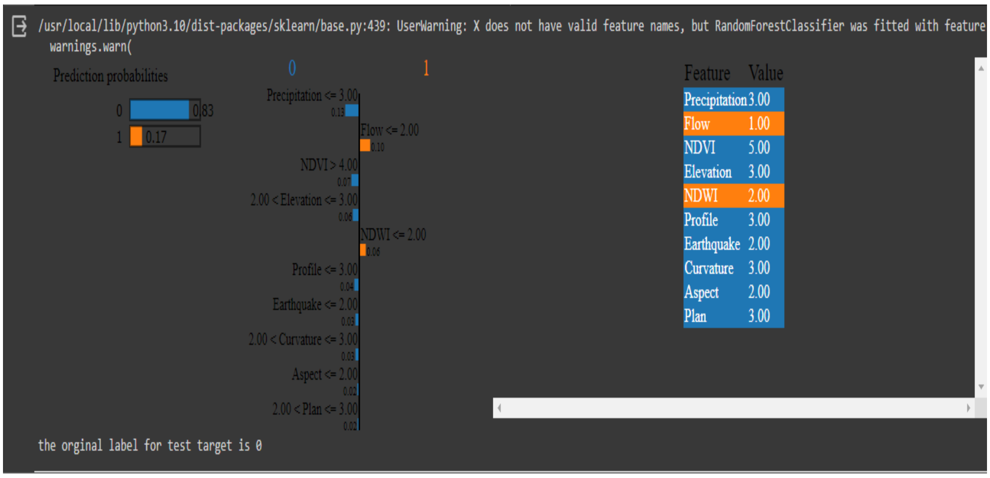
Work Done (30% Evaluation)



Work Done (30% Evaluation)

```python
exp = explainer.explain_instance(
    data_row=X_test.iloc[4],
    predict_fn=model.predict_proba,
    top_labels=0
)
#shows the prediction interpretation in the notebook environment: for a target class label as 1
exp.show_in_notebook(show_table=True)
print("the orginal label for test target is",y_test.iloc[4])
```


Work Done (30% Evaluation)



Work Done (30% Evaluation)

```
import numpy as np
import pandas as pd
#from sklearn import datasets

# Let's import the data from sklearn
#from sklearn.datasets import load_wine
#wine_db=load_wine()
landslide_db=pd.read_csv('landslide.csv')
#Conver to pandas dataframe
#landslide=pd.DataFrame(data=np.c_[landslide_db['data'],landslide_db['target']],columns=landslide_db['feature_names']+['target'])
print(landslide_db)
#Check data with info function
#landslide.info()
```

```
      Landslide  Aspect  Curvature  Earthquake  Elevation  Flow  Lithology  \
0             0       3          3           2          2     2          1
1             0       1          5           2          3     1          1
2             0       3          4           3          2     2          4
3             0       1          3           3          3     5          1
4             0       5          4           2          1     4          1
...         ...     ...        ...         ...        ...   ...        ...
1207          1       4          2           1          4     2          5
1208          1       4          5           1          5     3          5
1209          1       3          4           1          5     2          5
1210          1       2          2           1          3     1          1
1211          1       3          4           1          3     2          1

      NDVI  NDWI  Plan  Precipitation  Profile  Slope
0        4     2     2              3        3      2
1        4     2     5              5        2      2
2        3     2     4              5        2      2
3        2     4     3              5        3      3
4        2     4     3              3        1      4
...    ...   ...   ...            ...      ...    ...
1207     1     5     3              2        4      2
1208     1     5     5              2        1      5
1209     2     3     3              2        2      5
1210     5     1     1              1        3      3
1211     4     1     4              1        2      3

[1212 rows x 13 columns]
```

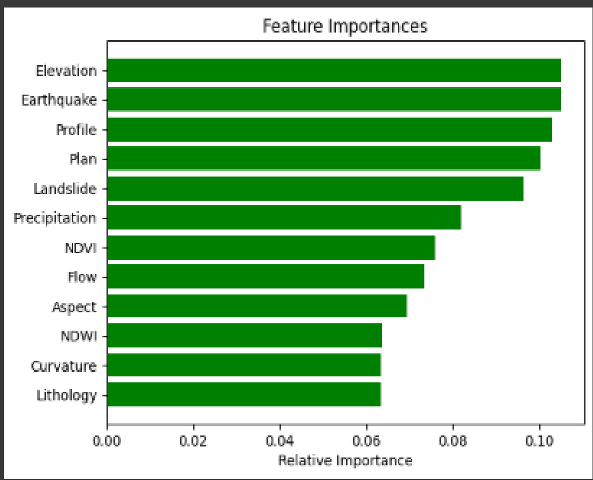

Work Done (30% Evaluation)

```
[3] from sklearn.model_selection import train_test_split

    X = landslide_db.drop('Landslide', axis=1)
    y = landslide_db['Landslide']

    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=0.2, random_state=42
    )
```

```
[4] from sklearn.ensemble import RandomForestClassifier

    model = RandomForestClassifier(random_state=42)
    model.fit(X_train, y_train)
    score = model.score(X_test, y_test)
```

Work Done (30% Evaluation)

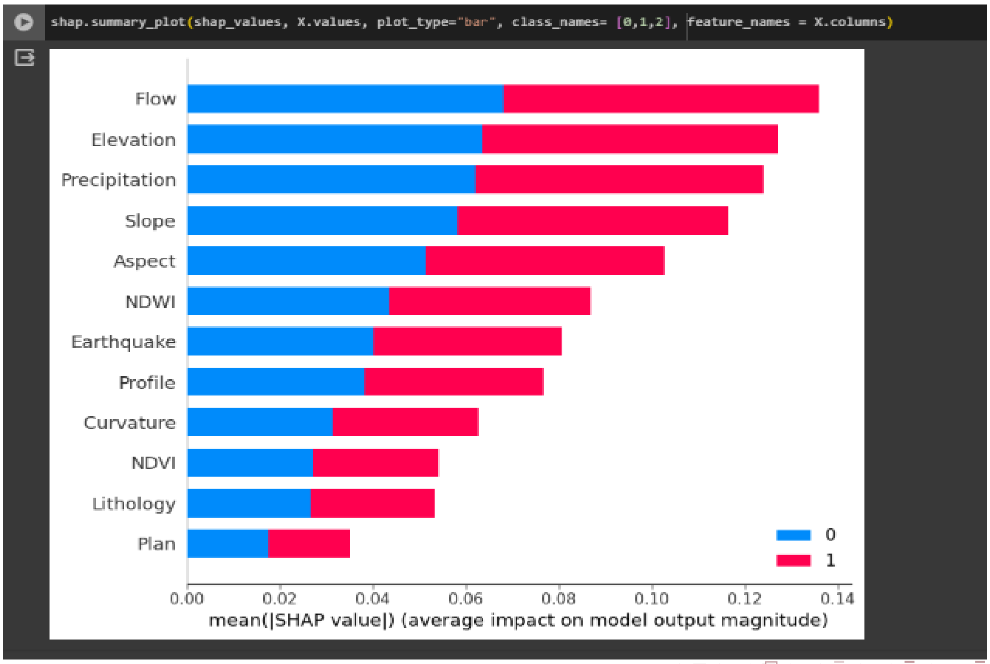
```python
import matplotlib.pyplot as plt
importances = model.feature_importances_
indices = np.argsort(importances)
features = landslide_db.columns
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='g', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



Work Done (30% Evaluation)

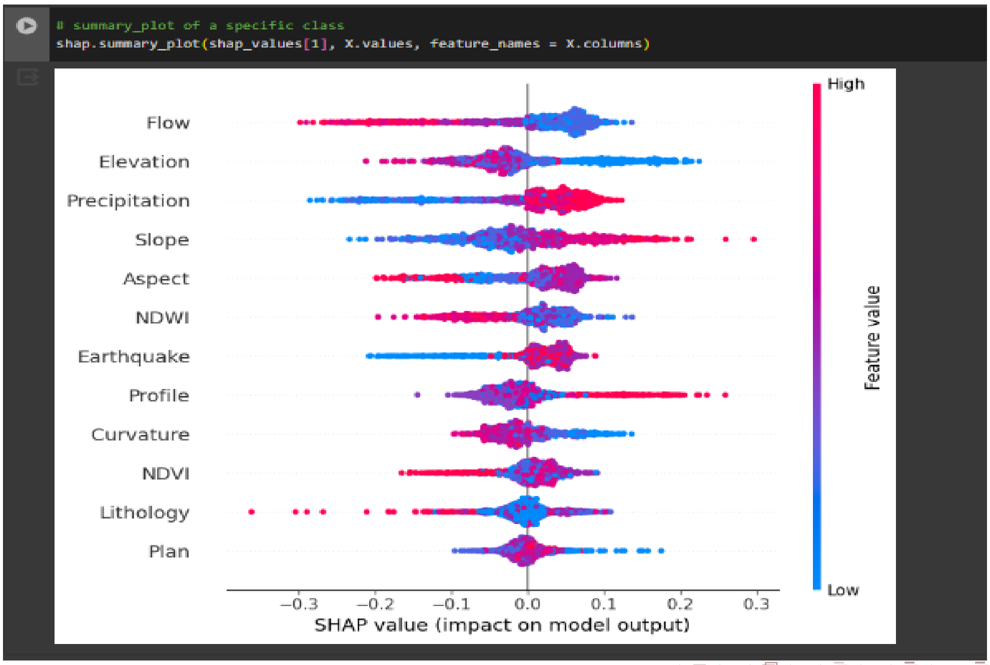
```
y.value_counts()

0    606
1    606
Name: Landslide, dtype: int64

[7] pip install shap

Collecting shap
  Downloading shap-0.44.0-cp310-cp310-manylinux_2_12_x86_64.manylinux2010_x86_64.manylinux_2_17_x86_64.manylinux2014_x86_64.whl (533 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 533.5/533.5 kB 3.8 MB/s eta 0:00:00
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from shap) (1.23.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from shap) (1.11.4)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (from shap) (1.2.2)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from shap) (1.5.3)
Requirement already satisfied: tqdm>=4.27.0 in /usr/local/lib/python3.10/dist-packages (from shap) (4.66.1)
Requirement already satisfied: packaging>20.9 in /usr/local/lib/python3.10/dist-packages (from shap) (23.2)
Collecting slicer==0.0.7 (from shap)
  Downloading slicer-0.0.7-py3-none-any.whl (14 kB)
Requirement already satisfied: numba in /usr/local/lib/python3.10/dist-packages (from shap) (0.58.1)
Requirement already satisfied: cloudpickle in /usr/local/lib/python3.10/dist-packages (from shap) (2.2.1)
Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in /usr/local/lib/python3.10/dist-packages (from numba->shap) (0.41.1)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas->shap) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas->shap) (2023.3.post1)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->shap) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->shap) (3.2.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1->pandas->shap) (1.16.0)
Installing collected packages: slicer, shap
Successfully installed shap-0.44.0 slicer-0.0.7

[8] import shap
    # compute SHAP values
    explainer = shap.TreeExplainer(model)
    shap_values = explainer.shap_values(X)
```

Work Done (30% Evaluation)

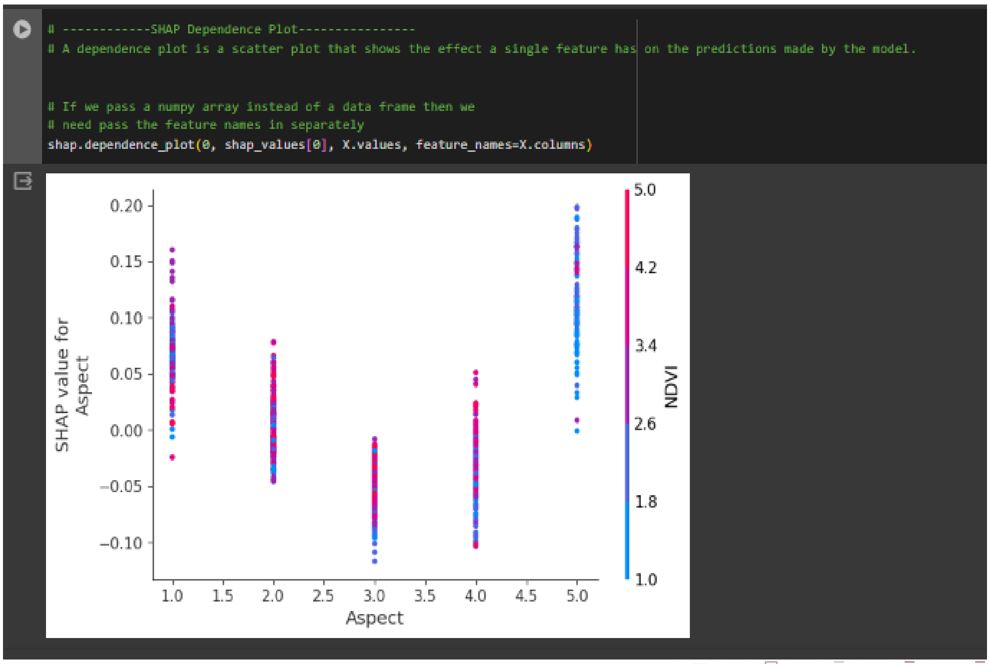


Phase II - Interim Evaluation II Landslide Prediction using XAI and Spatio-Temporal Knowledge

Work Done (30% Evaluation)

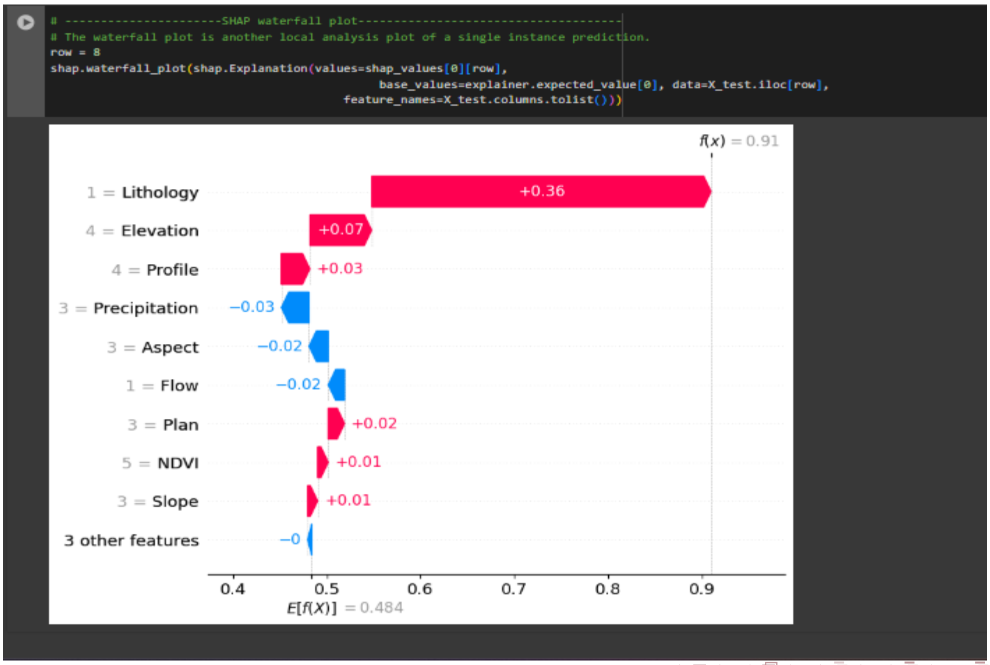


Work Done (30% Evaluation)

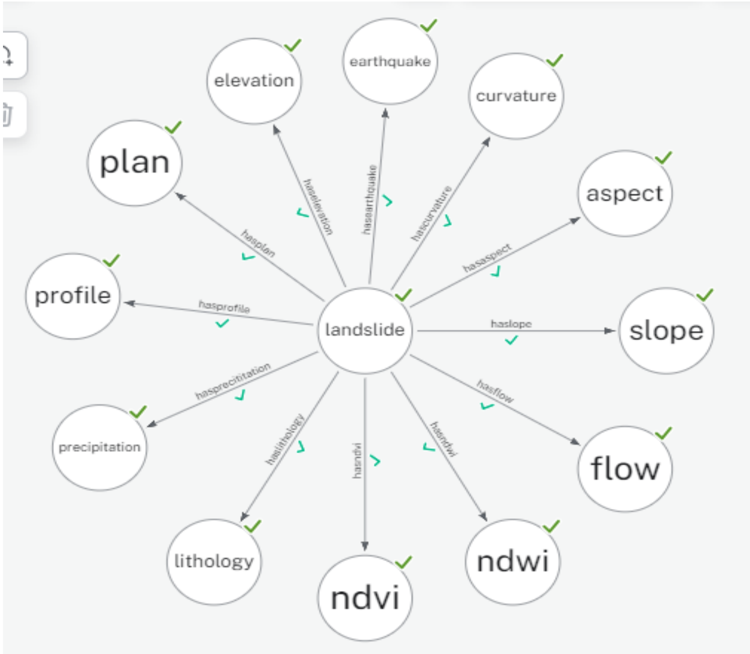


Phase II - Interim Evaluation II Landslide Prediction using XAI and Spatio-Temporal Knowledge

Work Done (30% Evaluation)

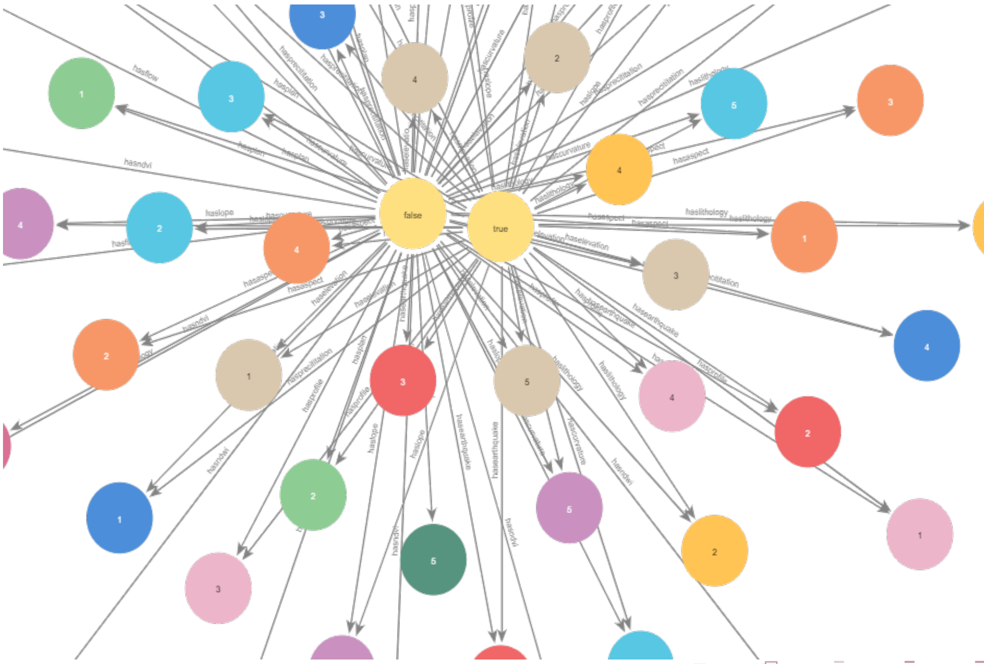


Work Done (60% Evaluation)



Work Done (60% Evaluation)

Work Done (60% Evaluation)

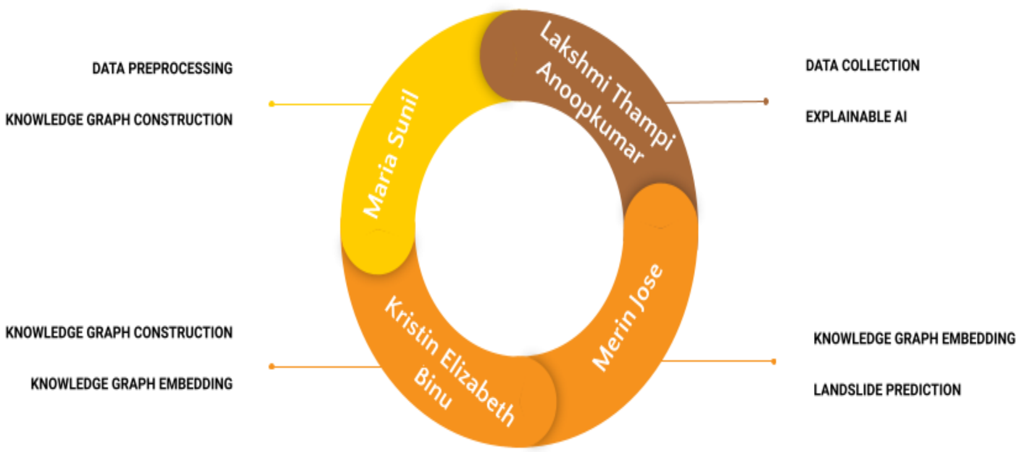


Results (100% Evaluation)

Future Scope

- **Real-Time Monitoring:** Develop capabilities for real-time monitoring of environmental factors and conditions that may contribute to landslide occurrences, allowing for proactive intervention and timely warnings to at-risk communities.
- **Integration with Disaster Management Systems:** Integrate the Landslide Prediction System with existing disaster management frameworks and emergency response systems to streamline communication, coordination, and resource allocation during landslide events.

Work Breakdown and Responsibilities



Conclusion

A method to predict Landslide using XAI and Spatio-Temporal Knowledge Graph is proposed which can be used for an early detection of landslide in hilly areas. This method can be adopted by the government for effective mitigation and preparedness measures.

References-I

[1] Chen, L.; Ge, X.; Yang, L.; Li, W.; Peng, L. An Improved Multi-Source Data-Driven Landslide Prediction Method Based on Spatio-Temporal Knowledge Graph. Remote Sens. 2023, 15, 2126.

[2] Ge, X.; Yang, Y.; Chen, J.; Li, W.; Huang, Z.; Zhang, W.; Peng, L. Disaster Prediction Knowledge Graph Based on Multi-Source Spatio-Temporal Information. Remote Sens. 2022, 14, 1214.

[3]R. Lijuan, L. Jun and G. Wei, "Multi-source Knowledge Embedding Research of Knowledge Graph," 2019 IEEE 3rd International Conference on Circuits, Systems and Devices (ICCSD), Chengdu, China, 2019, pp. 163-166

References-II

[4] Collini, E., Palesi, L.I., Nesi, P., Pantaleo, G., Nocentini, N. and Rosi, A., 2022. Predicting and understanding landslide events with explainable AI. IEEE Access, 10, pp.31175-31189.

[5]Pradhan, B., Dikshit, A., Lee, S. and Kim, H., 2023. An explainable AI (XAI) model for landslide susceptibility modeling. Applied Soft Computing, 142, p.110324.

[6] Xu, B.; Zhang, C.; Liu, W.; Huang, J.; Su, Y.; Yang, Y.; Jiang, W.; Sun, W. Landslide Identification Method Based on the FKGR-Net Model for Remote Sensing Images. Remote Sens. 2023, 15, 3407.

Phase II - Interim Evaluation II Landslide Prediction using XAI and Spatio-Temporal Knowledge

References-III

[7] Wang, C., Ma, X., Chen, J. and Chen, J., 2018. Information extraction and knowledge graph construction from geoscience literature. Computers geosciences, 112, pp.112-120.

[8] Ma, X., 2022. Knowledge graph construction and application in geosciences: A review. Computers Geosciences, 161, p.105082.

Status of Paper Publication

The research paper has been accepted and recommended for publication at the 3rd International Conference on Applied Artificial Intelligence and Computing – ICAAIC 2024, organized by R P Sarathy Institute of Technology, Salem, Tamil Nadu, India. The conference is scheduled to take place from June 05th to June 07th, 2024.

ICAAIC 2024 - Acceptance Letter Inbox ×

ICAAIC CONFERENCE <icaaic.contact@gmail.com> Apr 18, 2024, 12:16 PM
to Maria, preetha_kg, Kristin, me, Merin

Dear Author,

Hearty Congratulations!

Your paper has been accepted and recommended for publication at the 3rd International Conference on Applied Artificial Intelligence and Computing – ICAAIC 2024, organized by R P Sarathy Institute of Technology, Salem, Tamil Nadu, India. The conference is scheduled to take place from June 05th to June 07th, 2024.

Please refer the attachments:

- Acceptance Letter
- Technical Comments
- General Guidelines

Once your manuscript is accepted, author modifications will not be permitted

Last date for Registration: 27 April, 2024

Payment Link:
INR Link: https://www.townscript.com/v2/e/3rd-international-conference-on-applied-artificial-intelligence-and-computing-433004/booking/tickets

Registration Procedure: After the payment, kindly send the final paper, response to reviewer comments, IEEE copyright form and payment proof for registration confirmation.
For more details refer: https://www.icaaic.com/registration.php

Appendix B: Vision, Mission, Programme Outcomes and Course Outcomes

Vision, Mission, Programme Outcomes and Course Outcomes

Institute Vision

To evolve into a premier technological institution, moulding eminent professionals with creative minds, innovative ideas and sound practical skill, and to shape a future where technology works for the enrichment of mankind.

Institute Mission

To impart state-of-the-art knowledge to individuals in various technological disciplines and to inculcate in them a high degree of social consciousness and human values, thereby enabling them to face the challenges of life with courage and conviction.

Department Vision

To become a centre of excellence in Computer Science and Engineering, moulding professionals catering to the research and professional needs of national and international organizations.

Department Mission

To inspire and nurture students, with up-to-date knowledge in Computer Science and Engineering, ethics, team spirit, leadership abilities, innovation and creativity to come out with solutions meeting societal needs.

Programme Outcomes (PO)

Engineering Graduates will be able to:

1. Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern Tool Usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and Team work: Function effectively as an individual, and as a member or leader in teams, and in multidisciplinary settings.

10. Communication: Communicate effectively with the engineering community and with society at large. Be able to comprehend and write effective reports documentation. Make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team. Manage projects in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSO)

A graduate of the Computer Science and Engineering Program will demonstrate:

PSO1: Computer Science Specific Skills
The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills
The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills
The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

Course Outcome 1: Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).

Course Outcome 2: Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).

Course Outcome 3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).

Course Outcome 4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).

Course Outcome 5: Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).

Course Outcome 6: Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

Appendix C: CO-PO-PSO Mapping

CO-PO AND CO-PSO MAPPING

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
CO1	2	2	2	1	2	2	2	1	1	1	1	2	3		
CO2	2	2	2		1	3	3	1	1		1	1		2	
CO3									3	2	2	1			3
CO4					2			3	2	2	3	2			3
CO5	2	3	3	1	2							1	3		
CO6					2			2	2	3	1	1			3

3/2/1: high/medium/low

JUSTIFICATIONS FOR CO-PO MAPPING & CO-PSO MAPPING

MAPPING	LOW/MEDIUM/ HIGH	JUSTIFICATION
100003/ CS722U.1-PO1	M	Knowledge in the area of technology for project development using various tools results in better modeling.
100003/ CS722U.1-PO2	M	Knowledge acquired in the selected area of project development can be used to identify, formulate, review

		research literature, and analyze complex engineering problems reaching substantiated conclusions.
100003/ CS722U.1-PO3	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO4	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO5	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.1-PO6	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.1-PO7	M	Project development based on societal and environmental context solution identification is the need for sustainable development.
100003/ CS722U.1-PO8	L	Project development should be based on professional ethics and responsibilities.
100003/ CS722U.1-PO9	L	Project development using a systematic approach based on well defined principles will result in teamwork.

100003/ CS722U.1-PO10	M	Project brings technological changes in society.
100003/ CS722U.1-PO11	H	Acquiring knowledge for project development gathers skills in design, analysis, development and implementation of algorithms.
100003/ CS722U.1-PO12	H	Knowledge for project development contributes engineering skills in computing & information gatherings.
100003/ CS722U.2-PO1	H	Knowledge acquired for project development will also include systematic planning, developing, testing and implementation in computer science solutions in various domains.
100003/ CS722U.2-PO2	H	Project design and development using a systematic approach brings knowledge in mathematics and engineering fundamentals.
100003/ CS722U.2-PO3	H	Identifying, formulating and analyzing the project results in a systematic approach.
100003/ CS722U.2-PO5	H	Systematic approach is the tip for solving complex problems in various domains.
100003/ CS722U.2-PO6	H	Systematic approach in the technical and design aspects provide valid conclusions.

100003/ CS722U.2-PO7	H	Systematic approach in the technical and design aspects demonstrate the knowledge of sustainable development.
100003/ CS722U.2-PO8	M	Identification and justification of technical aspects of project development demonstrates the need for sustainable development.
100003/ CS722U.2-PO9	H	Apply professional ethics and responsibilities in engineering practice of development.
100003/ CS722U.2-PO11	H	Systematic approach also includes effective reporting and documentation which gives clear instructions.
100003/ CS722U.2-PO12	M	Project development using a systematic approach based on well defined principles will result in better teamwork.
100003/ CS722U.3-PO9	H	Project development as a team brings the ability to engage in independent and lifelong learning.
100003/ CS722U.3-PO10	H	Identification, formulation and justification in technical aspects will be based on acquiring skills in design and development of algorithms.
100003/ CS722U.3-PO11	H	Identification, formulation and justification in technical aspects provides the betterment of life in various domains.
100003/ CS722U.3-PO12	H	Students are able to interpret, improve and redefine technical aspects with mathematics, science and

		engineering fundamentals for the solutions of complex problems.
100003/ CS722U.4-PO5	H	Students are able to interpret, improve and redefine technical aspects with identification formulation and analysis of complex problems.
100003/ CS722U.4-PO8	H	Students are able to interpret, improve and redefine technical aspects to meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
100003/ CS722U.4-PO9	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.4-PO10	H	Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools for better products.
100003/ CS722U.4-PO11	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.4-PO12	H	Students are able to interpret, improve and redefine technical aspects for demonstrating the knowledge of, and need for sustainable development.

100003/ CS722U.5-PO1	H	Students are able to interpret, improve and redefine technical aspects, apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.5-PO2	M	Students are able to interpret, improve and redefine technical aspects, communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
100003/ CS722U.5-PO3	H	Students are able to interpret, improve and redefine technical aspects to demonstrate knowledge and understanding of the engineering and management principle in multidisciplinary environments.
100003/ CS722U.5-PO4	H	Students are able to interpret, improve and redefine technical aspects, recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.
100003/ CS722U.5-PO5	M	Students are able to interpret, improve and redefine technical aspects in acquiring skills to design, analyze and develop algorithms and implement those using high-level programming languages.
100003/ CS722U.5-PO12	M	Students are able to interpret, improve and redefine technical aspects and contribute their engineering skills in

		computing and information engineering domains like network design and administration, database design and knowledge engineering.
100003/ CS722U.6-PO5	M	Students are able to interpret, improve and redefine technical aspects and develop strong skills in systematic planning, developing, testing, implementing and providing IT solutions for different domains which helps in the betterment of life.
100003/ CS722U.6-PO8	H	Students will be able to associate with a team as an effective team player for the development of technical projects by applying the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
100003/ CS722U.6-PO9	H	Students will be able to associate with a team as an effective team player to Identify, formulate, review research literature, and analyze complex engineering problems
100003/ CS722U.6-PO10	M	Students will be able to associate with a team as an effective team player for designing solutions to complex engineering problems and design system components.
100003/ CS722U.6-PO11	M	Students will be able to associate with a team as an effective team player, use research-based knowledge and research methods including design of experiments, analysis and interpretation of data.

100003/ CS722U.6-PO12	H	Students will be able to associate with a team as an effective team player, applying ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.1-PSO1	H	Students are able to develop Computer Science Specific Skills by modeling and solving problems.
100003/ CS722U.2-PSO2	M	Developing products, processes or technologies for sustainable and socially relevant applications can promote Programming and Software Development Skills.
100003/ CS722U.3-PSO3	H	Working in a team can result in the effective development of Professional Skills.
100003/ CS722U.4-PSO3	H	Planning and scheduling can result in the effective development of Professional Skills.
100003/ CS722U.5-PSO1	H	Students are able to develop Computer Science Specific Skills by creating innovative solutions to problems.
100003/ CS722U.6-PSO3	H	Organizing and communicating technical and scientific findings can help in the effective development of Professional Skills.