Artificial Intelligence Enhanced Pipeline Route Optimization

B. Tech. Project Report

Submitted by

Mihika Dravid	**112003038**
Shrushti Garde	**112003041**
Mihika Sanghvi	**112003084**

Under the guidance of

Prof. Soma Ghosh

COEP Technological University, Pune

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

COEP TECHNOLOGICAL UNIVERSITY, PUNE-5

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING,

COEP TECHNOLOGICAL UNIVERSITY, PUNE-5

CERTIFICATE

Certified that this project titled, "Artificial Intelligence Enhanced Pipeline Route Optimization" has been successfully completed by

Mihika Dravid	**112003038**
Shrushti Garde	**112003041**
Mihika Sanghvi	**112003084**

and is approved for the partial fulfillment of the requirements for the degree of "B.Tech. Computer Engineering".

SIGNATURE	SIGNATURE
Prof. Soma Ghosh	**Dr. Pradeep Deshmukh**
Project Guide	**Head**
Department of CSE	**Department of CSE**
COEP Tech Pune,	**COEP Tech Pune,**
Shivajinagar, Pune - 5.	**Shivajinagar, Pune - 5.**

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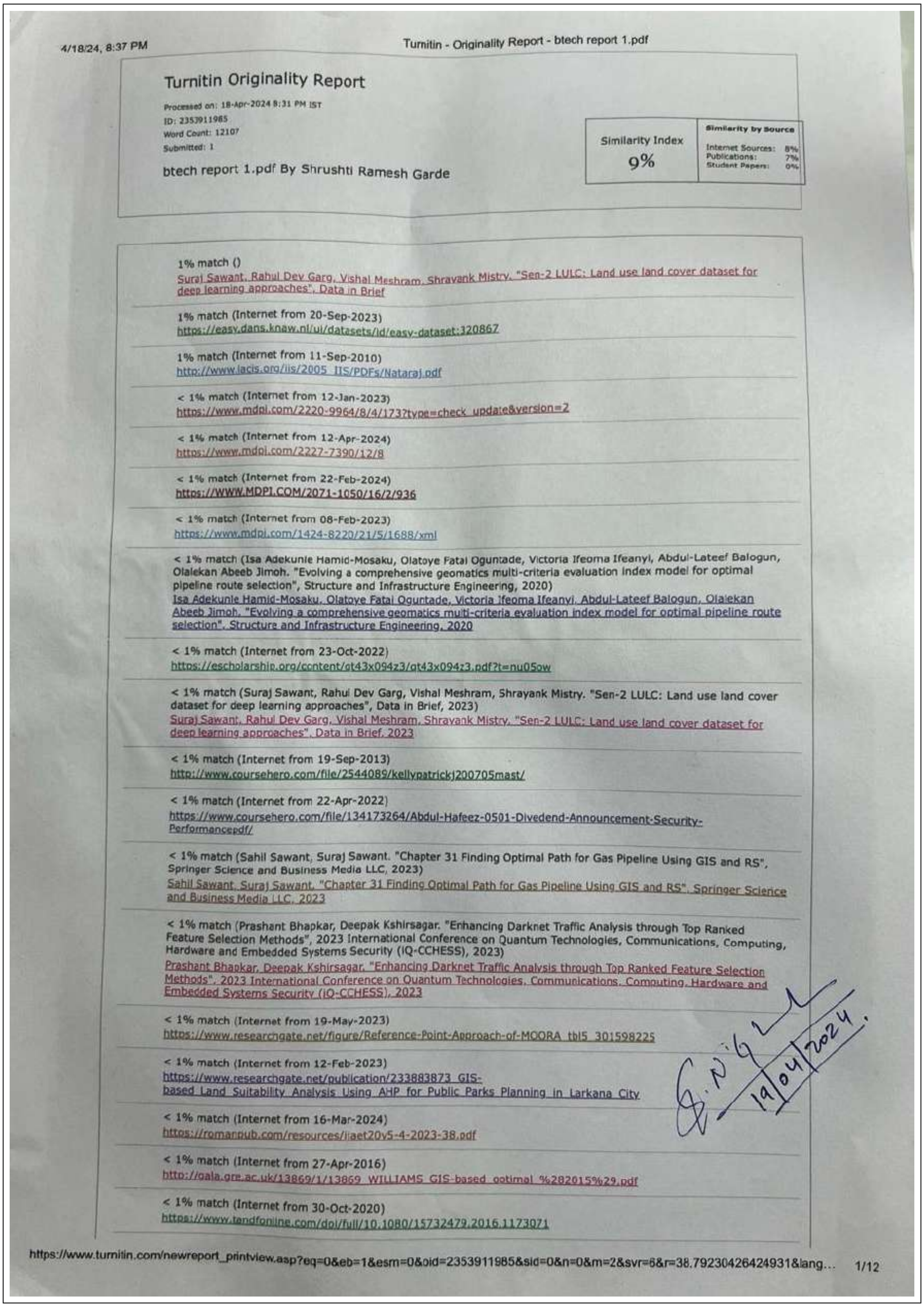

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Abstract

The development of efficient and cost-effective pipeline routes is crucial for the energy industry, necessitating strategic planning to determine optimal paths. This project endeavors to address this need by designing an intelligent pipeline route optimization system that integrates Geographic Information Systems (GIS), Remote Sensing (RS) technologies, machine learning models, and Multi-Criteria Decision-Making (MCDM) techniques. Leveraging advanced technologies and methodologies, such as machine learning and deep learning models, the research seeks to enhance the accuracy of classifying and analyzing geospatial datasets, ultimately contributing valuable insights to geographical information systems, remote sensing, and infrastructure planning.

The evolution of pipeline route selection methodologies highlights a progression from early GIS-based models to more integrated and sophisticated approaches over the decades. While challenges persist, including data limitations and technical hurdles, the project's methodology adopts a comprehensive and integrated approach to overcome these obstacles. By leveraging AI and DL techniques coupled with GIS-based spatial multicriteria decision-making methods, the research aims to push the boundaries of accuracy in pipeline route optimization. This study examines the Dadri-Panipat Network in the North and the Hazira-Ankleshwar Pipeline in the West, showcasing the versatility of the approach across diverse pipeline networks in India.

The limitations of current LULC methods include a lack of integration of advanced deep learning (DL) models, training on region-specific datasets leading to biased performance, and under-representation of certain LULC classes. To address these limitations, this study utilizes the Sentinel-2 LULC dataset, comprising over 213,750 pre-processed 10 m resolution images rep-

resenting seven distinct classes of Land Use Land Cover, thereby representing a diverse and versatile region. Six deep learning models are employed for training and testing: LinkNet Inceptionv3, LinkNet ResNet152, UNet ResNext101, UNet Inception ResNetv2, UNet DenseNet169, and UNet EfficientNetb7 with accuracies ranging from 92%-96%. The performance of these models is compared to determine the most suitable model for LULC classification, which can subsequently be employed for further route planning applications. The UNet EfficientNetb7 model emerged as the best-performing, with high training accuracy and validation accuracy.

The study employed Multi-Criteria Decision-Making and Analytic Hierarchy Process (AHP) to prioritize route selection factors systematically. Various AI heuristics, including Dijkstra's Algorithm and A* algorithm variants, were used for route optimization, aiming to minimize pipeline length while considering land use/land cover (LULC) priorities. In the implementation of AHP, the relative importance of seven LULC classes was determined, with urban areas, dense forests, farms, and water bodies identified as crucial. Dijkstra's Algorithm efficiently allocated the pipeline through barren lands and sparse forests, achieving the most optimized route.

In the Dadri-Panipat study area, the original pipeline length was approximately 206.22 kilometers, while the optimized distance ranged from 143.17 to 150.44 kilometers, showcasing notable reductions in pipeline length. Similarly, in the Hazira-Ankleshwar study area, the original pipeline route spanned approximately 90 kilometers, whereas the optimized distances ranged from around 55 to 77.65 kilometers. The study highlights the significance of adopting an interdisciplinary approach for sustainable and environmentally conscious infrastructure development, paving the way for intelligent approaches in pipeline optimization.

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Chapter 1

Introduction

1.1 Opening Section

The overall field of pipeline construction has long been a cornerstone of the oil and gas industry, representing a significant investment in infrastructure. Pipelines are the arteries through which valuable resources are transported, making them indispensable for the industry's operations. However, this sector has faced enduring challenges stemming from diverse climatic and soil conditions. These conditions pose substantial risks to pipeline integrity, with the potential for pipe ruptures and catastrophic oil spills, causing environmental harm and threatening the well-being of nearby communities (Ansa and Akinrotimi, 2018).

In response to these challenges, there has been a notable evolution in the approach to pipeline construction, culminating in the emergence of intelligent pipeline route optimization. Recognizing the need for comprehensive planning that accounts for technical, environmental, and safety factors, the field of intelligent pipeline route optimization has developed to address these challenges [11]. It is during the planning, design, and construction phases that this discipline comes into play, aiming to ensure that the chosen route optimally balances cost-effectiveness with safety and environmental responsibility.

This project addresses the challenge of developing a cost-effective and environmentally friendly pipeline route optimization technique. It focuses on integrating and leveraging Geographic Information Systems (GIS) and Remote Sensing (RS) technologies, alongside machine learning models and Multi-Criteria Decision-Making (MCDM) methodologies. The problem at hand is to create an intelligent system that, through accurate land cover classification and MCDM-driven least-cost path determination, minimizes the environmental impact and project costs associated with pipeline construction.

1.2 Background

1.2.1 Broad Overview

Intelligent Route Optimization of gas pipelines represents a paradigm shift in the management and operation of critical energy infrastructure. At its core, this innovative approach seeks to enhance the efficiency, reduce costs, and minimize the environmental footprint of gas transportation networks. Today, due to dynamic economies, rapid population growth, and the growing demands of countries for energy, the importance of natural gas pipelines is increasing [3]. By harnessing the power of advanced technologies such as artificial intelligence, machine learning, and deep learning, intelligent route optimization aims to revolutionize how gas pipelines are planned, operated, and maintained.

The primary objectives of this optimization process extend beyond mere logistical efficiency. This type of study aims to ascertain all the criteria and possible risks to realize the route that is most suitable and has the least environmental cost in terms of land use [7]. It responds to the increasing demands for sustainable energy practices and heightened environmental awareness. As the world grapples with the challenges of climate change, optimizing the routes of gas pipelines becomes not only a matter of economic prudence but a crucial step towards building a more sustainable and eco-friendly energy infrastructure. This transformative approach considers factors ranging from real-time demand fluctuations to geographic and environmental considerations, ensuring a dynamic and responsive system that adapts to the complexities of the modern energy landscape. The significance of intelligent route optimization is not confined to its immediate operational impact. Still, it resonates with the broader goals of energy security, environmental stewardship, and pursuing a more sustainable energy future.

1.2.2 Contextual factors

Intelligent route optimization of gas pipelines operates within a dynamic landscape shaped by various factors, including political, social, environmental, economic, and restrictive considerations. Cost reduction is a key objective, necessitating both environmental sustainability and economic viability. Technologies like artificial intelligence, GIS, and deep learning offer promising solutions for achieving these goals, aiding decision-making with tools for cost analysis, environmental impact assessment, and site location.

Market dynamics, such as fluctuating energy prices and demands, also influence route optimization strategies. Adaptability to changing market conditions is crucial for maintaining cost-effectiveness and competitiveness in the evolving energy market. Additionally, there's a growing emphasis on reducing carbon footprints and transitioning to cleaner energy sources, driving the integration of intelligent route optimization to enhance operational and environmental performance.

Geopolitical factors, including energy security and international relations, further shape pipeline planning. Intelligent optimization serves as a tool for navigating the complex geopolitical landscape and ensuring a reliable and secure energy supply chain. This multifaceted approach addresses the diverse challenges of pipeline route planning in today's interconnected world.

1.2.3 History

One of the main reasons for building an intelligent and efficient pipeline route is to avoid any serious incidents that can harm life and the economy. One example of a catastrophic industrial disaster is the Bhopal Gas Tragedy, which occurred on the night of December 2-3, 1984. The incident took place at the Union Carbide India Limited (UCIL) pesticide plant in Bhopal, Madhya Pradesh, India. A toxic gas, methyl isocyanate (MIC), leaked from the plant, exposing over half a million people to lethal chemicals. The immediate aftermath was devastating, with thousands losing their lives within days. This is in line with the observation that pipeline infrastructure poses a high security risk to the environment and communities, and is of international concern[. In the context of economic development, optimized pipeline routes are essential for fostering industrial growth. Efficient energy transportation ensures a stable and reliable supply for industries, promoting economic activities and job creation.

Chapter 2

Literature Review

In recent decades, the field of pipeline route optimization has witnessed significant advancements, driven by the integration of Geographic Information Systems (GIS), Remote Sensing (RS) technologies, and innovative decision-making approaches. Initially, the challenge lay in effectively incorporating decision-makers' preferences into route selection processes. Piotr Jankowski's model in 1994 addressed this by proposing a systematic approach to site or route selection, leveraging GIS for multi-criteria evaluation [12]. However, limitations persisted, such as the model's reliance on basic spatial processing operations and the struggle to fully integrate non-spatial data and decision-makers' preferences.

Sandra C. Feldman and colleagues introduced a more sophisticated enhancement to land suitability mapping in 1995, utilizing advanced technologies like Landsat Thematic Mapper and SPOT satellite imagery [8]. This approach showed significant improvements, particularly in regions with limited map resources or usage restrictions. However, project-specific adjustments and considerations of actual project costs were necessary for its implementation.

The integration of digital pipelines with remote sensing images and GIS technology, as proposed by Zhu Xiaoge and Dong Wentong in 2002, revolutionized oil pipeline management [26]. Subsequently, the POMA project in 2004 aimed to streamline decision-making for large-diameter transmission pipeline construction in urban areas, emphasizing the role of GIS technology [14].

In the realm of GIS-based route optimization, studies by various researchers have contributed significantly to refining methodologies and addressing practical challenges. For instance, in 2011, Ahmad M. Salah and Denis Atwood introduced a GIS-based application for pipeline route analysis that moved beyond optimizing for a single criterion like distance [21]. This dynamic and multidimensional decision matrix allowed for the analysis and ranking of multiple potential routes based on accumulated weights of individual segments, offering a more comprehensive optimization process.

In 2012, Eftychia C. Marcoulaki and colleagues extended research on pipeline route optimization by integrating advanced optimization technologies with geographical information, process simulators, and equipment databases [16]. Their approach considered various factors, including hydraulics, equipment cost, reliability, and landscape information, leading to diverse optimal pipeline routing and equipment design features. The incorporation of stochastic optimization enhanced the method's robustness in adapting to uncertainties and variations.

Similarly, the introduction of the Analytic Hierarchy Process (AHP) into GIS-based oil and gas pipeline route selection by Jianhua Wan and colleagues improved decision-making by considering qualitative factors alongside quantitative ones [25]. This comprehensive approach addressed influential factors of the pipeline, such as slopes, geological conditions, and surface features, leading to more informed route selection decisions.

The research landscape expanded further with studies exploring innovative methodologies and technologies for pipeline route optimization. In 2019, George Triebel and Todd Crouthamel introduced a GIS-based approach for route selection, employing a weighted ranking analysis to consider construction, utility, and cost impacts [24]. Ali İhsan Durmaz and colleagues presented an automatic pipeline route design approach using AHP, Least-Cost Path Analysis (LCPA), and GIS, resulting in significant reductions in cost and other metrics [7]. Linlin Zhao and others introduced an integrated BIM-GIS method for water distribution system planning, showcasing the potential for advanced project planning and execution [27].

Continued advancements in pipeline route optimization have seen the emergence of comprehensive geomatics multi-criteria evaluation index models, A* algorithms, and GIS spatial optimization methods [11, 17, 10]. These methodologies leverage diverse data sources and analytical techniques to address environmental, economic, and technical considerations, offering robust solutions for pipeline route selection challenges.

The integration of machine learning, remote sensing, and other advanced technologies has further enhanced the intelligence and accuracy of pipeline route optimization methods. Studies exploring the application of genetic algorithms, fuzzy logic, and Laplacian smoothing algorithms have demonstrated promising results in optimizing pipeline routes while navigating obstacles and uncertainties [6, 5, 13].

Future research should address challenges in accurately evaluating seismic hazards, incorporating expert preferences, and managing uncertainties in decision-making, while considering economic, social, and environmental aspects, and enhancing stakeholder engagement and decision support systems to advance pipeline route optimization.

Chapter 3

Research Gaps and Problem Statement

3.1 Research and Literature Gaps

Although 80% of the data can be georeferenced, there is a gap in understanding the challenges, limitations, and quality assurance measures for georeferenced data. Research should explore best practices for ensuring data accuracy and reliability when integrating GIS into pipeline route planning. The research in the status quo discusses the need for integrating risk factors in GIS-based route planning but does not delve into specific methodologies or tools for quantifying and managing risk and uncertainty. Future research can explore robust risk assessment models and approaches, particularly in complex marine and dynamic shipping environments. Although various GIS tools and models are mentioned, there is a gap in the literature regarding comprehensive comparative studies that evaluate the strengths, weaknesses, and suitability of different GIS tools and models for specific project types and regions.

Firstly, the current state of pipeline route alignment underscores the intricacy of the process, marked by the analysis of extensive data and a multitude of parameters contingent upon the distance between source and destination. The sheer complexity arises as the pipeline network expands, demanding meticulous attention to available computing resources or necessitating a reduction in the desired number of iterations or potential routes. Despite the sophistication required in such a complex system, there exists a noticeable research gap concerning the under-utilization of advanced heuristic algorithms for route optimization, specifically within the realm of gas pipelines.

Secondly, in current studies, there is a noticeable deficit in the application of automated and intelligence-based approaches, particularly when considering the utilization of open-source tools. The literature reflects a gap in the availability of comprehensive, automated solutions that harness the power of artificial intelligence and intelligent algorithms to optimize the pipeline route alignment process. The existing state of research falls short of providing robust methodologies that seamlessly integrate these advanced technologies, leaving a void in the field. Consequently, there is a compelling research gap that calls for the exploration and development of sophisticated methods capable of automating and infusing intelligence into the intricate process of gas pipeline route planning.

Thirdly, the present research acknowledges the paramount significance of high-resolution datasets in enhancing the accuracy of route alignment systems, emphasizing their role as crucial components of the decision-making process. However, there remains a research gap that warrants exploration and deeper investigation into the specific impact of integrating high-resolution datasets. While the existing literature recognizes their importance in a general sense, there is a need for more nuanced insights into how these datasets influence the accuracy of decision-making in route alignment systems.

Fourthly, in the current state of research on land use and land cover classification, there is a significant gap pertaining to the integration of advanced deep learning models, specifically convolutional neural networks (CNNs) and recurrent neural networks (RNNs). While machine learning techniques have been applied to these tasks, the potential benefits of deep learning models, known for their prowess in image recognition, remain largely untapped. To address this research gap, future studies should focus on exploring advanced data augmentation techniques within the context of land use and land cover classification. Techniques like generative adversarial networks (GANs) can be leveraged to create synthetic training data, enhancing the robustness and generalization of classification models. Additionally, there is a need for optimization of deep learning models for real-time and efficient land use classification.

Further, environmental impact assessment is necessary for this study. In the current state of research, there is a collective acknowledgment of the paramount importance of minimizing environmental impact in the planning of pipeline and linear projects.

3.2 Problem Statement

This project addresses the challenges of developing an environmentally friendly and cost-effective pipeline route optimization technique. It focuses on integrating and leveraging Geographic Information Systems (GIS) and Remote Sensing (RS) technologies, alongside machine learning models and Multi-Criteria Decision-Making (MCDM) methodologies.

This research aims to design and develop an intelligent pipeline route optimization system that leverages Geographic Information Systems (GIS), Remote Sensing (RS) technologies, deep learning models, and heuristic techniques.

3.3 Objectives

To achieve the research aim, several critical objectives have been identified. Firstly, the research involves the meticulous collection, organization, and analysis of complex data, including satellite imagery and various geospatial datasets. These datasets are sourced from different organizations and government institutions, demanding careful selection, storage, and analysis. Geographic Information System (GIS) emerges as a pivotal technological tool in this context, facilitating the integration, storage, and analysis of spatial relationships among different layers of data.

Secondly, the process of determining the optimal pipeline route is heavily influenced by factors related to land use, especially in the context of constructing long-distance pipelines. These factors and their sub-factors must be meticulously identified to assign priorities, ultimately leading to the development of a well-suited route. Furthermore, the research recognizes the significant role of land use in the project's planning process hence necessitating LULC classification. To address this, state-of-the-art classification algorithms, such as artificial neural networks (ANNs), support vector machines (SVMs), random forest (RF), and classification and regression trees (CART), have been used in the past.

In addition, the research explores GIS-based spatial multi-criteria decision-making (S-MCDM) methods to support complex decision-making with multiple objectives. The accurate assignment of weights and rankings to factors influencing GIS pipeline routing is vital for project success. These factors, often derived from literature, expert consultation, and site surveys, can be numerous and sometimes conflicting. Various multi-criteria decision-making (MCDM) methods have been developed for this purpose, including the Delphi process, Scoring, Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), and Data Envelopment Analysis (DEA) [11]. These methods facilitate the assessment and prioritization of factors to inform informed decision-making in pipeline routing.

Lastly, the research employs GIS's least-cost path analysis (LCPA) to find suitable land corridors for linear infrastructures. This grid-based GIS algorithm evaluates various criteria relevant to pipeline routing, calculating their relative importance using multiple criteria evaluation (MCE) techniques. It then identifies viable routes between two geographical points within the defined corridors of interest. Collectively, these objectives contribute to the research's overarching aim of enhancing intelligent pipeline route optimization through informed decision-making.

3.4 Scope

This project's scope is specifically confined to onshore pipeline projects, focusing on pipelines located above the Earth's surface. Consequently, the analysis is limited to factors and sub-factors relevant to the design phase of such pipelines. The primary objective is to identify an optimal corridor through which the pipeline will traverse, emphasizing route alignment. It's important to note that this research does not encompass the design or construction aspects of the pipeline once the route has been selected. The project's focus remains dedicated to the preliminary phases of pipeline planning and alignment.

Chapter 4

Methodology

4.1 Introduction

The specific problem statement revolves around the necessity for a cost-effective and environmentally friendly pipeline route optimization technique. Traditional approaches to pipeline construction often overlook the intricate interplay of technical, environmental, and safety factors, leading to sub-optimal routes and increased risks. The integration of Geographic Information Systems (GIS) and Remote Sensing (RS) technologies, coupled with machine learning models and Multi-Criteria Decision-Making (MCDM) methodologies, emerges as a promising avenue to address these challenges.

The aim of the research is clear and focused—to design and implement an intelligent pipeline route optimization system. This system is envisioned to be a sophisticated amalgamation of cutting-edge technologies, with GIS and RS providing a spatial context, machine learning models enhancing data analysis, and MCDM techniques facilitating decision-making based on multiple criteria. The primary objective is twofold: to offer a solution that is not only cost-effective but also minimizes the environmental impact associated with pipeline construction.

The core technical challenge lies in optimizing the least-cost path analysis.

By employing advanced algorithms, the research aims to develop a system that intelligently navigates through various factors, including topography, land cover, and environmental sensitivity, to identify the optimal route. This not only ensures cost-effectiveness but also minimizes the ecological footprint of pipeline construction.

4.2 Methodological Approach

In the initial phase of our route optimization research, the pivotal first step involves downloading satellite imagery. To commence, we meticulously define our Area of Interest (AOI), pinpointing the specific region or pipeline route under scrutiny. Following this, we carefully select the most suitable satellite imagery source, considering factors like resolution, frequency, and spectral bands to align with our research objectives. Subsequently, we download the images, ensuring adherence to file formats and metadata requirements. Once obtained, the data undergoes preprocessing, including tasks like calibration and correction. This organized and verified dataset then serves as the foundational element for our intelligent pipeline route optimization analysis, integrating GIS, remote sensing, and machine learning methodologies.

In crafting our intricate AI approach for optimizing pipeline routes, the initial step is the judicious download of satellite imagery, laying the foundation for a comprehensive analysis of the study area. The process unfolds with a meticulous identification of the study area, involving preprocessing of Sentinel-2 (Sentil) L2A data. This entails a vigilant noise check and the identification of Land Use and Land Cover (LULC) classes specific to the Indian region, with a deliberate exclusion of snow and wetlands. A literature survey follows, refining our understanding of these classes and ensuring alignment with the latest research developments.

In the intricate process of Land Use Land Cover (LULC) classification tailored for the Indian region, we meticulously define classes to align with the unique environmental dynamics of this diverse landscape. Our focus includes excluding wetlands and snow-covered areas, steering clear of water bodies, and deliberately avoiding the complexities associated with urban areas. Emphasizing the significance of environmental considerations, we specifically target barren lands devoid of substantial vegetation cover. By tailoring our classification to these contextual exclusions, our approach ensures a nuanced understanding of the land use dynamics in the Indian region, laying the foundation for precise and region-specific intelligent pipeline route optimization.

The second facet of the methodology involves the application of the Analytic Hierarchy Process (AHP). This multicriteria decision-making technique provides a structured framework for weighing and prioritizing the identified criteria and sub-criteria. AHP plays a pivotal role in refining the decision-making process, ensuring that factors influencing route selection are systematically evaluated. The integration of AHP injects a layer of precision and rationality into the decision-making, aligning the chosen route with a nuanced understanding of diverse criteria.

The culmination of the methodology resides in the realm of route optimization. Here, the study pioneers into less-explored territory by incorporating Artificial Intelligence (AI) techniques and Deep Learning (DL) models. This avant-garde approach holds the promise of significantly enhancing the accuracy and efficiency of route selection. The intricate interplay of AI and DL, coupled with heuristic functions tailored for Least Cost Path Analysis (LCPA), forms the crux of this innovative stage. It involves harnessing machine learning algorithms to intelligently analyze geospatial datasets and predict the optimal route, thereby pushing the boundaries of what traditional methods can achieve. In essence, the methodology unfolds as a meticulously crafted triad, seamlessly transitioning from foundational LULC analysis through systematic AHP application, ultimately culminating in the cutting-edge domain of AI-driven route optimization. This holistic approach encapsulates the intricacies of pipeline route planning, marrying conventional GIS methods with the transformative potential of contemporary and AI-driven techniques. The flowchart illustrating the steps taken throughout our project process can be found in Figure 4.1, providing a visual representation of the project workflow and decision-making process.

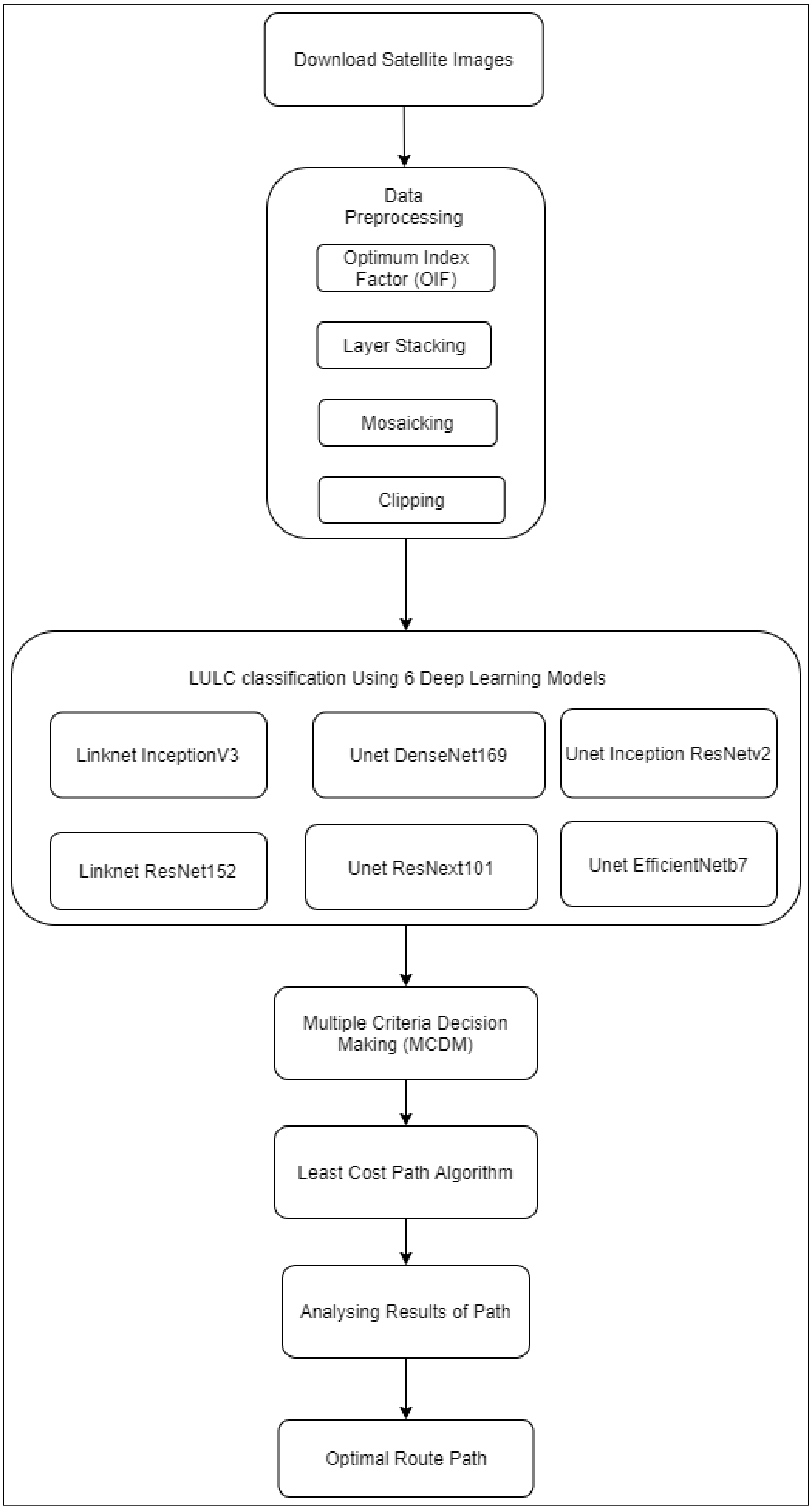

Figure 4.1: Methodology Flowchart

4.2.1 Data Collection and Analysis

The Copernicus Open Access Hub offers free and unrestricted access to products from the Sentinel mission, including Sentinel-1, Sentinel-2, Sentinel-3, and Sentinel-5P, for users to download. We downloaded atmospherically corrected Sentinel-2 L2A images from December 2023. Parameters such as platform, processing level, cloud cover, acquisition dates, and region of interest were used to download the necessary satellite images for our study area. Sentinel-2 tiles were acquired by manually downloading them from the Copernicus Hub.

4.2.2 Study Area

This study focuses on two significant pipelines in India: the Dadri-Panipat Network in the northern region (originally 200km long) and the Hazira-Ankleshwar Pipeline in the western region (originally 90km long) as shown in figure 4.2 and figure 4.3 respectively. The selection of these specific study areas serves a twofold purpose. Firstly, it underscores the versatility and adaptability of our analytical approach across distinct pipeline networks, showcasing its relevance and effectiveness in varying geographical contexts.

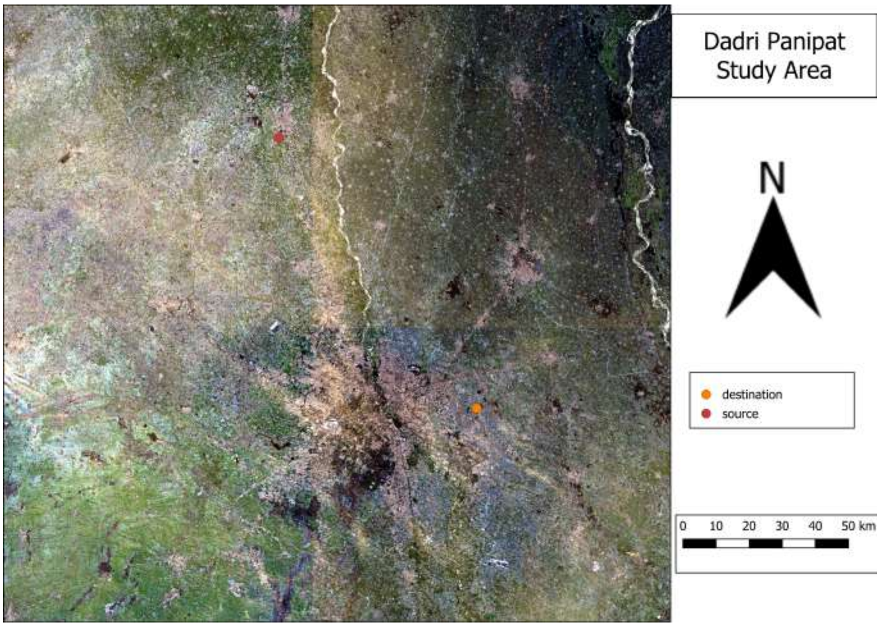

Figure 4.2: Dadri-Panipat Study Area

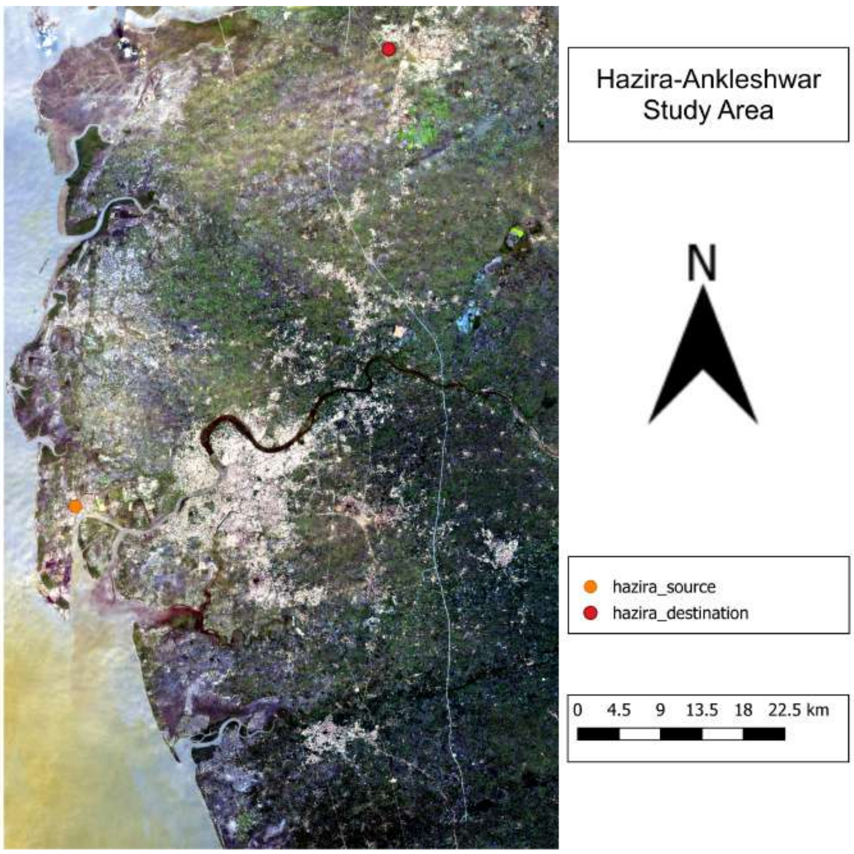

Figure 4.3: Hazira-Ankleshwar Study Area

Secondly, the deliberate inclusion of the Dadri-Panipat Network, strategically located in the North, and the Hazira-Ankleshwar Pipeline, significant in the West, adds depth and breadth to our study. By focusing on these strategically important regions, we not only bolster the credibility of our research but also underscore the broader applicability and relevance of our methodology to diverse regions and pipeline systems spanning the country.

As depicted in Table 4.1, the tiles obtained from Copernicus were Sentinel-2A tiles. Specifically, Hazira-Ankleshwar necessitated the retrieval of a single tile, while Dadri-Panipat required four tiles. Subsequently, the RGB bands (Band 2, 3, 4) were carefully chosen, stacked, and mosaicked to align with the requirements.

Table 4.1: Sentinel-2A Images

Satellite	**Tile ID**	**Date of Acquisition**	**Cloud Cover**	**Study Area**
Sentinel-2A	43BQD	08-12-2023	0.058016	Hazira-Ankleshwar
Sentinel-2A	43RFN	05-12-2023	0.000096	Dadri-Panipat
Sentinel-2A	43RGN	05-12-2023	0.000129	Dadri-Panipat
Sentinel-2A	43RGM	05-12-2023	0.000186	Dadri-Panipat
Sentinel-2A	43RFM	05-12-2023	0.000259	Dadri-Panipat

4.2.3 Data Preprocessing

The downloaded Sentinel-2 L2A satellite images have already undergone atmospheric correction and require minimal pre-processing. Each tile contains 13 bands with varying resolutions from 10 m to 60 m.

Pre- processing involves several steps

- OIF : To select the best three bands, we calculate the Optimum Index Factor (OIF) statistic value. Bands B4, B3, and B2 are chosen based on the maximum OIF value.

- Layer-stacking: Layer-stacking merges the selected bands into a single image with multiple layers, each layer representing a different band. This allows for easier analysis and visualization of different spectral bands in the study area.

- Mosaicking: This process combines individual tiles for each band to create a single, larger image. It helps to create a seamless image of the study area by removing the visible edges between adjacent tiles.

- Clipping: Clipping crops the image to the study area, removing any unnecessary parts of the image. This step helps to focus the analysis on the specific area of interest and reduces the file size of the image dataset.

4.2.4 LULC Classification

We have determined seven Land Use and Land Cover (LULC) classes: barren land, water bodies, sparse and dense forest, built-up areas, fallow land, and agricultural land. In our research, we will employ six deep learning models, training them on a dataset for land use and land cover (LULC) classification. Subsequently, we will compare their performance metrics to identify the most effective model for this task. Details of the seven Land Use Land Cover classes can be found in Table 5.1

4.2.5 Models

We have included six models: Linknet Inceptionv3, Linknet ResNet152, Unet DenseNet169, Unet ResNext101, Unet Inception Resnetv2, and Unet EfficientNetb7 for Land Use Land Cover classification. These models were selected because they have not been extensively used in the field of Land Use Land Cover (LULC) classification and have been introduced relatively recently.

Choosing models that have not been widely used in the LULC domain is crucial for several reasons. Firstly, it allows for the exploration of new approaches and methodologies in LULC classification, potentially leading to improved accuracy and efficiency. Secondly, using newer models can help in staying abreast of the latest advancements in deep learning and computer vision, ensuring that the research is at the forefront of technological development. Lastly, by using models that are not commonly employed in LULC classification, the research can contribute to expanding the knowledge base and diversifying the range of models available for similar applications in the future.

To better understand model optimization and performance evaluation, we have also considered total parameters, trainable parameters, and non-trainable parameters for each of the models. Specific details for each model are given in Table 4.2.

Table 4.2: Comparison of different models based on total, trainable, and non-trainable parameters

Model	**Total parameters**	**Trainable Parameters**	**Non-Trainable Parameters**
Linknet Inceptionv3	26,269,126	26,228,678	40,448
Linknet ResNet152	63,518,191	63,366,665	151,526
Unet ResNext101	51,282,351	51,142,505	139,846
Unet Inception Resnetv2	62,062,278	61,999,750	62,528
Unet DenseNet169	19,520,550	19,360,166	160,384
Unet EfficientNetb7	75,048,822	74,736,118	312,704

Linknet Inceptionv3 combines the LinkNet architecture with the Inceptionv3 backbone, known for its effectiveness in image classification tasks.

LinkNet is chosen for its ability to produce high-quality segmentation masks, making it suitable for LULC classification where precise delineation of land cover classes is crucial. Inceptionv3's feature extraction capabilities help the model learn rich spatial and spectral features from satellite imagery, enhancing classification accuracy [2].

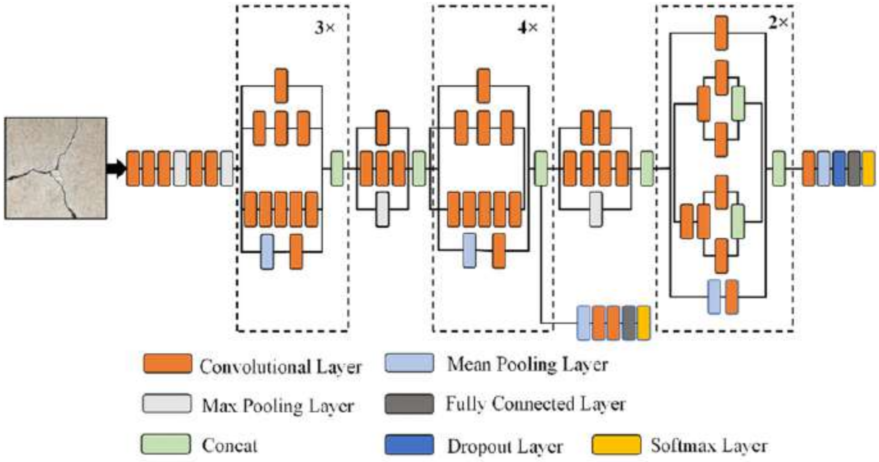

Figure 4.4: Linknet Inceptionv3 [2]

Linknet Resnet 152, which consists of LinkNet with the ResNet152 backbone, is selected for its deeper architecture, allowing it to capture more complex patterns in satellite imagery. ResNet152's skip connections help mitigate the vanishing gradient problem, enabling more effective training and better feature representation in the model. This combination is suitable for LULC classification tasks that require high-resolution imagery and fine-grained classification [19].

Unet Densenet169 combines the Unet architecture with DenseNet169 backbone and is chosen for its densely connected layers, enabling the model to learn intricate spatial relationships in satellite imagery. DenseNet's dense connections facilitate feature reuse and encourage feature propagation, improving the model's ability to capture detailed land cover features. This model is well-suited for LULC classification tasks where detailed feature ex-

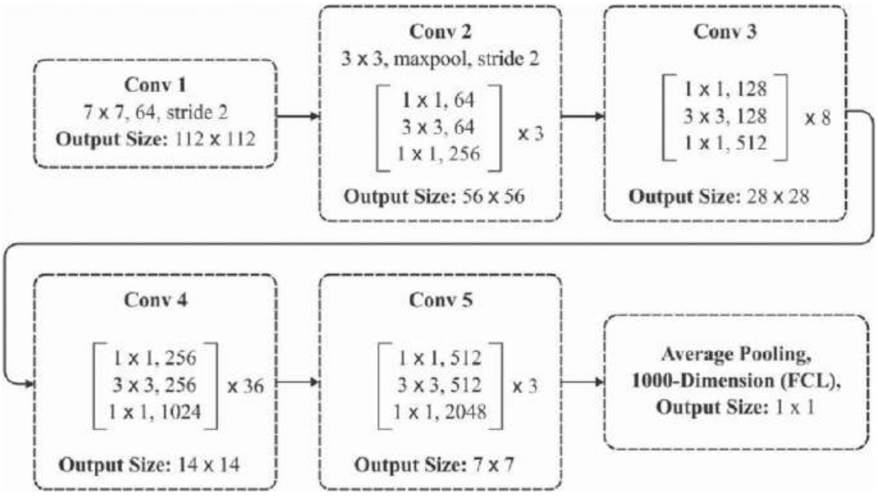

Figure 4.5: Linknet Resnet152 [19]

traction is essential, such as distinguishing between different types of vegetation or urban features [15].

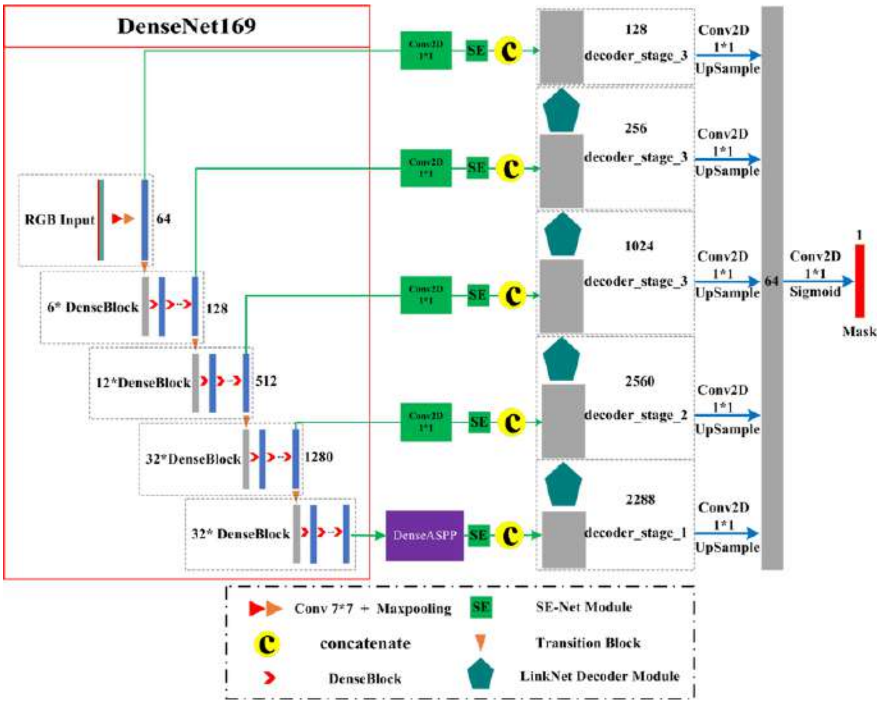

Figure 4.6: Unet Densenet169 [15]

Unet Resnext101 consisting of Unet with the ResNext101 backbone is selected for its high computational efficiency and strong performance in image recognition tasks. ResNext101's cardinality parameter allows the model to capture diverse spatial patterns and spectral characteristics in satellite imagery, enhancing classification accuracy. This model is suitable for LULC classification tasks that require a balance between computational efficiency and high performance.

Unet Inception Resnetv2 combines the Unet architecture with the Inception ResNetv2 backbone, known for its exceptional performance in image recognition tasks. Inception ResNetv2's multi-scale feature extraction capabilities help the model capture both local and global features in satellite imagery, improving classification accuracy. This combination is ideal for LULC classification tasks that require precise delineation of land cover classes and robust feature extraction from high-resolution imagery [18].

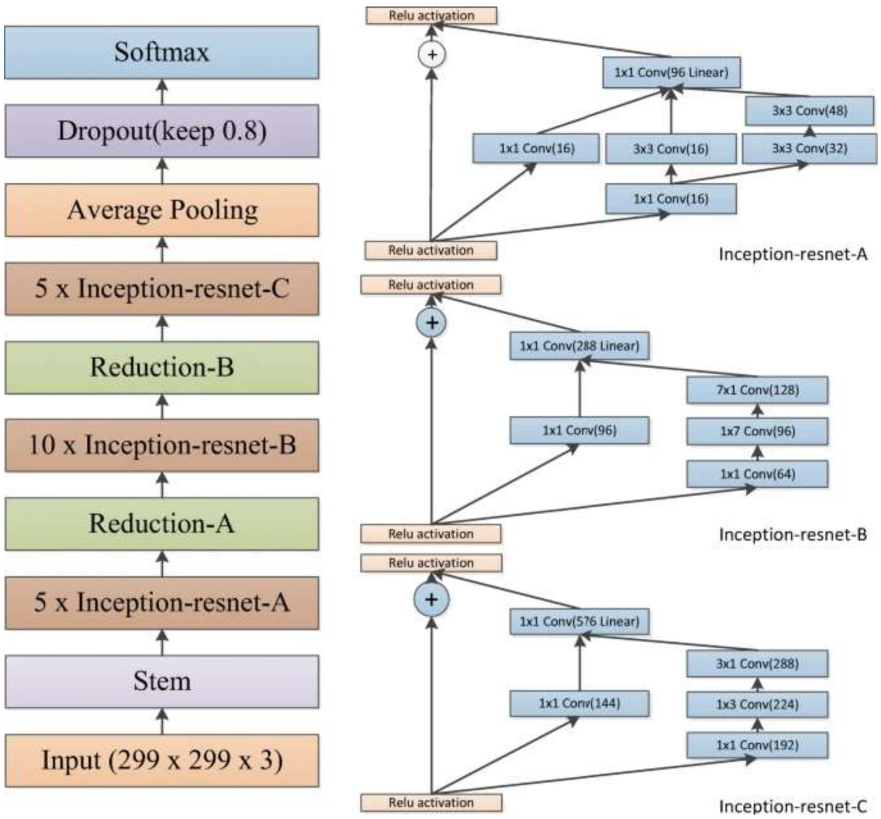

Figure 4.7: Unet Inception Resnetv2 [18]

Unet Efficientnetb7 contains Unet with the EfficientNetb7 backbone and is chosen for its efficiency and scalability, allowing it to handle large-scale satellite imagery datasets. EfficientNetb7's compound scaling method enables the model to achieve state-of-the-art performance with fewer parameters, reducing computational complexity. This model is suitable for LULC classification tasks that involve processing large volumes of satellite imagery while maintaining high classification accuracy [1].

Figure 4.8: Unet Efficientnetb7 [1]

4.2.6 Multi Criteria Decision Making - AHP

In this study, the Analytic Hierarchy Process (AHP) is integrated into the Geographic Information System (GIS) framework to enhance the pipeline route decision-making process. AHP facilitates the establishment of hierarchical structure models [25]. By incorporating AHP within the GIS, decision makers gain a systematic approach to evaluate and prioritize various criteria involved in pipeline route selection.

The application of AHP involves structuring the decision problem into hierarchical levels. At Level I, the overarching goal or focus of the decision is defined, while Level II encompasses the factors or criteria pertinent to the decision-making process [20]. The prioritization process is achieved by assigning numerical values from a scale of 1-9 developed by Saaty to represent the importance of each criterion. Pairwise comparisons of these attributes are conducted using a matrix-based approach, facilitating systematic calculation and analysis.

The scale of relative importance for pairwise comparison as developed by Saaty is shown in Table 4.3 [20].

Table 4.3: Pairwise Combination Scale for AHP

Intensity	Definition	Explanation
1	Equal importance	Two activities contribute equally to the object
3	Moderate importance	Slightly favors one over another
5	Essential or strong importance	Strongly favors one over another
7	Demonstrated importance	Dominance of the demonstrated in practice
9	Extreme importance	Evidence favoring one over another of highest possible order of affirmation
2,4,6,8	Intermediate values	When compromise is needed

4.2.7 Route Optimization

For Route optimization, Least Cost Path Analysis (LCPA) heuristics were used for guiding pathfinding algorithms toward efficient and optimal routes within a spatial network. LCPA heuristics, part of a class of computational methods, iteratively evaluate potential paths to identify the route with the lowest accumulated cost, considering factors like terrain, environmental impact, and construction expenses. These algorithms are essential in the energy sector for designing pipeline networks that minimize transportation costs, enhance reliability, and adhere to safety and environmental standards. By leveraging LCPA heuristics, gas pipeline route optimization becomes a streamlined process, addressing spatial challenges effectively to optimize pipeline designs [23].

In our project, we implemented and utilized five distinct heuristic functions to facilitate Least Cost Path Analysis (LCPA) for optimizing pipeline routing. Each heuristic function serves as a crucial component within path finding algorithms, guiding the exploration of solution spaces to identify the most cost-effective routes.

Firstly, we employed the A* Chebyshev Distance heuristic, which is particularly effective in grid-based spaces due to its ability to evaluate movement costs uniformly in horizontal, vertical, and diagonal directions. This metric aids in estimating the maximum difference between coordinates, facilitating efficient exploration of potential routes, especially in scenarios where movement constraints are uniform or where direct paths are sought after.

Next, we integrated the A* Diagonal heuristic, which extends the traditional A* algorithm by considering both straight-line (diagonal) and horizontal/vertical paths. This heuristic, leveraging a modified Euclidean distance formula, strikes a balance between accuracy and computational efficiency, making it ideal for optimizing pipeline routes through grid-based landscapes.

Furthermore, we applied the A* with Euclidean Distance heuristic, leveraging Euclidean distance calculations to estimate straight-line distances between nodes. This heuristic is valuable in guiding the A* algorithm efficiently towards optimal paths while considering the geometric aspects of the landscape.

In addition, we utilized the A* with Manhattan Distance heuristic, which estimates distances by summing absolute differences in horizontal and vertical positions. This heuristic aligns well with grid-based landscapes typical in pipeline routing scenarios, enabling efficient exploration of solution spaces while balancing computational efficiency and optimality.

Finally, we implemented Dijkstra's Distance as a foundational algorithm adaptable to various cost considerations inherent in pipeline routing. This algorithm systematically explores nodes based on cumulative distances, dynamically adapting to changes in costs or terrain features to generate optimal routes across diverse landscapes [9] [4].

We employed five distinct heuristic functions within the context of pipeline routing optimization and systematically compared their results to determine the most optimal approach. By implementing heuristics such as A* Chebyshev Distance, A* Diagonal, A* with Euclidean Distance, A* with Manhattan Distance, and Dijkstra's Distance, we aimed to evaluate and contrast the effectiveness of each heuristic in identifying the least cost paths for pipeline routes. Alongside evaluating the optimality of the paths generated by each heuristic, we scrutinized the spatial characteristics of these paths based on terrain types or other relevant classes. This approach allowed us to gain deeper insights into how different heuristics interacted with varying landscape features, providing a more comprehensive understanding of their performance beyond just path length. This comparative study allowed us to assess the strengths and weaknesses of each heuristic method, ultimately identifying the most effective heuristic approach for optimizing pipeline routing based on our specific project requirements and objectives.

Chapter 5

Experimental Setup

5.1 Requirements

5.1.1 Dataset

The Dataset used is "Sen-2 LULC Dataset" which is a collection of 2,13,750+ satellite images. [22]

1. Pre-processed 10 m resolution images representing 7 distinct classes of Land Use Land Cover. The 7 classes are water, Dense forest, Sparse forest, Barren land, Built up, Agriculture land, and Fallow land.

2. The Sentinel-2 images of Central India are taken from Copernicus Open Access Hub with cloud clover percentage ranging from 0 to 0.5%.

3. The images are a combination of bands B4, B3, and B2 constituting the red, green, and blue bands with a spectral resolution of 10m.

4. The dataset has 6 folders which are distributed in the following manner:

   - Training images - 149600 images
   - Training masks - 149600 images
   - Validation images - 32079
   - Validation masks - 32079

- Test images - 32079
- Test masks - 32079

For Land Use Land Cover Classification, we have identified seven classes, the details of which are given in Table 5.1

Table 5.1: LULC Classes

Class Label	**Class Denotation**	**Description**
0	Unclassified	Pixel that is not classified is assigned an unclassified name and zero label.
1	Water Bodies	Water from streams, rivers, lakes and reservoirs
2	Dense Forest	Area where tree canopy density is between 40% and 70%.
3	Built up	Artificial/concrete surface
4	Agriculture Land	Area where crops are cultivated or planted vegetation.
5	Barren land	Land where crops or plants cannot be cultivated due to soil infertility.
6	Fallow land	Land under agricultural cultivation but currently kept uncultivated
7	Sparse Forest	Area where tree canopy density is between 10% and 40%.

5.1.2 Preprocessing

The satellite images for the 2 study areas were downloaded from Copernicus Browser. The initial steps like Optimum Index Factor(OIF), stacking, and mosaicking are done on QGIS. QGIS is a robust and versatile open-source GIS software widely utilized for spatial analysis, mapping, and data visualization.

With its intuitive user interface and extensive feature set, QGIS empowers users to efficiently manage, edit, and analyze various types of geospatial data, including vector and raster formats. Its comprehensive suite of tools enables users to perform geoprocessing tasks, such as buffering, overlay analysis, and interpolation, facilitating complex spatial analysis and modeling.

5.1.3 Models

Training of all 6 models was done on Kaggle. It is a popular platform for hosting a wide range of challenges and projects where participants can collaborate and compete to solve real-world problems using machine learning and data analysis techniques. We utilized Kaggle's free GPU, and hence we were able to perform large computations in 10-11 hours with the help of GPU P100. This helped us enable faster model training and experimentation for tackling large-scale datasets and complex machine-learning tasks.

5.1.4 SuperDecisions Software

SuperDecisions is a powerful software tool designed specifically for implementing the Analytic Hierarchy Process (AHP) methodology in decision-making processes. AHP is a structured approach used to analyze and prioritize alternatives based on multiple criteria, making it ideal for complex decision problems across various industries. SuperDecisions facilitates this process by allowing users to create hierarchical models that organize decision criteria, alternatives, and sub-criteria in a logical tree-like structure. This visual representation helps users systematically break down decision problems into manageable components, fostering clarity and transparency in the decision-making process.

One of the key features of SuperDecisions is its support for pairwise comparisons. Through intuitive interfaces, users can perform pairwise comparisons between decision elements to determine their relative importance or performance. SuperDecisions incorporates algorithms to calculate priority weights based on these comparisons, providing quantitative insights into the significance of each criterion and alternative within the decision hierarchy. The software also includes consistency checking mechanisms to ensure the reliability of the pairwise comparison data, helping users identify and resolve inconsistencies that could affect the accuracy of the final priorities.

Chapter 6

Results and Discussion

6.1 Model Analysis for LULC

The results showcase the models' strong performance in training and validation, with the Unet EfficientNetb7 model standing out with the highest accuracy. This model achieved a training accuracy of 0.96 and a validation accuracy of 0.956, indicating its effectiveness in learning the dataset's features and generalizing well to new data. The Linknet Inceptionv3, Unet DenseNet169, and Unet Inception Resnetv2 models also performed exceptionally well, with training accuracies above 0.94 and validation accuracies above 0.94. These results suggest that these models are well-suited for the task of Land Use Land Cover classification.

On the other hand, the Linknet ResNet152 and Unet ResNext101 models achieved slightly lower accuracies, with training accuracies around 0.926-0.933 and validation accuracies around 0.923-0.929. Despite these slightly lower accuracies, these models still demonstrate strong performance and are competitive with the other models. Overall, the results highlight the effectiveness of these deep learning models in classifying Land Use Land Cover and the importance of selecting appropriate architectures for the task. Table 6.1 shows the training and validation metrics for the six models.

The confusion matrices of the three best-performing models namely: Efficientnetb7, Inceptionv3, and Resnet Inceptionv2. Unet Efficientnetb7 demonstrates high precision, recall, overall accuracy, F1 score, and MCC across most land cover classes. Particularly, it excels in predicting Barren land, with precision, recall, and F1 score above 0.9, indicating strong performance. However, the model struggles relatively more with Sparse forests, showing lower precision, recall, and F1 score compared to other classes. Despite this, its overall accuracy remains decent at 0.84, suggesting effectiveness in land-use land-cover classification as shown in Figure 6.4.

On the other hand, Unet Inceptionv3 exhibits varied performance across different classes. While it performs relatively well in predicting Water Class, with metrics above 0.8 as shown in Figure 6.5, it struggles notably with Barren land and Urban land. This indicates difficulty in accurately identifying these classes, potentially impacting its generalization to certain land cover types. Despite this variability, the model maintains a relatively high overall accuracy, though its performance varies significantly across different classes.

Similarly to Unet Efficientnetb7, Unet Inception Resnetv2 performs consistently well across most classes, with high precision, recall, overall accuracy, F1 score, and MCC. However, it also shows relatively lower performance in predicting Urban Land, with metrics below 0.7 as shown in Figure 6.6, indicating challenges in accurately classifying this land cover type. Overall, Unet Inception Resnetv2 demonstrates robust performance across various land cover classes, with room for improvement in certain classes like Urban Land.

Interestingly, all three models struggle in predicting the Urban class compared to other classes. Despite this challenge, Unet Efficientnetb7 and Unet Inception Resnetv2 demonstrate relatively better performance compared to

Unet Inceptionv3 in terms of overall accuracy. Unet Efficientnetb7 consistently achieves high overall accuracy across all classes, followed closely by Unet Inception Resnetv2. Unet Inceptionv3, however, exhibits more variability in performance across classes, with some showing notably lower precision, recall, and F1 score compared to others.

In summary, while all three models have their strengths and weaknesses, Unet Efficientnetb7 and Unet Inception Resnetv2 show more consistent performance across different land cover classes compared to Unet Inceptionv3. Despite common challenges in accurately classifying Urban Land, these models demonstrate effectiveness in land-use land-cover classification, with potential for further improvement in certain classes.

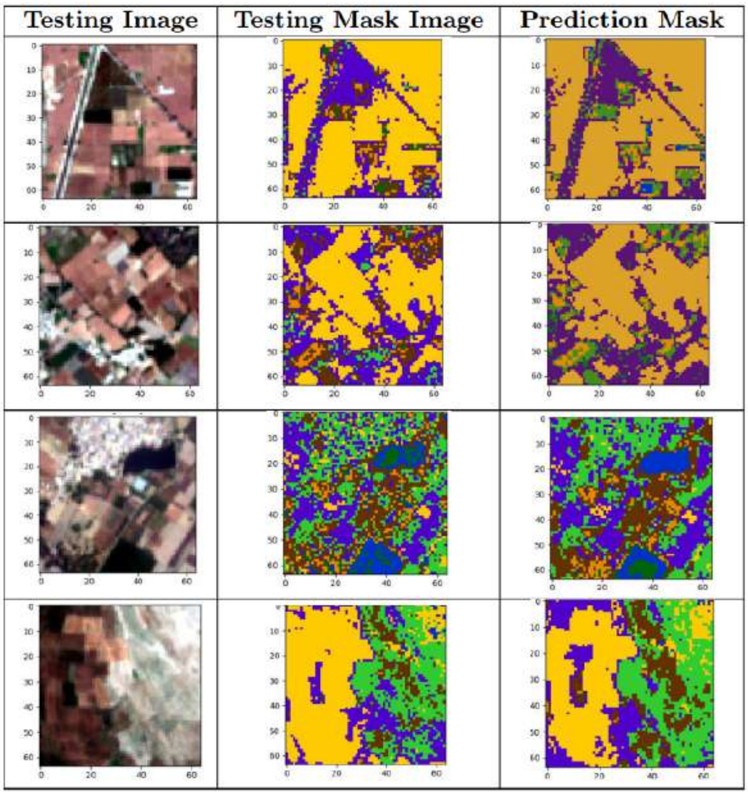

Figure 6.1: Unet-EfficientNetb7 Model: Testing Images and Predicted Masks

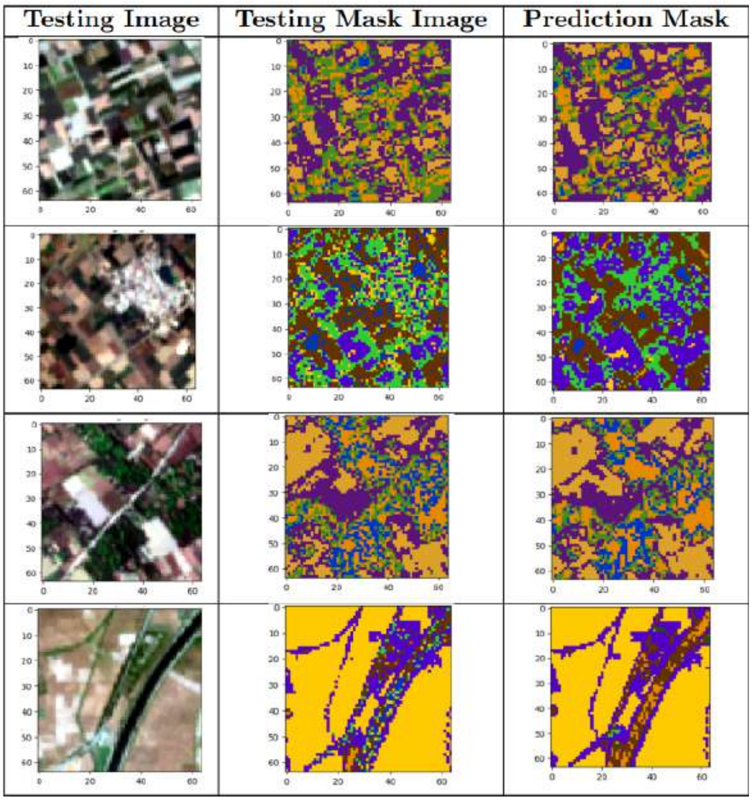

Figure 6.2: Unet-Inception Resnetv2 Model: Testing Images and Predicted Masks

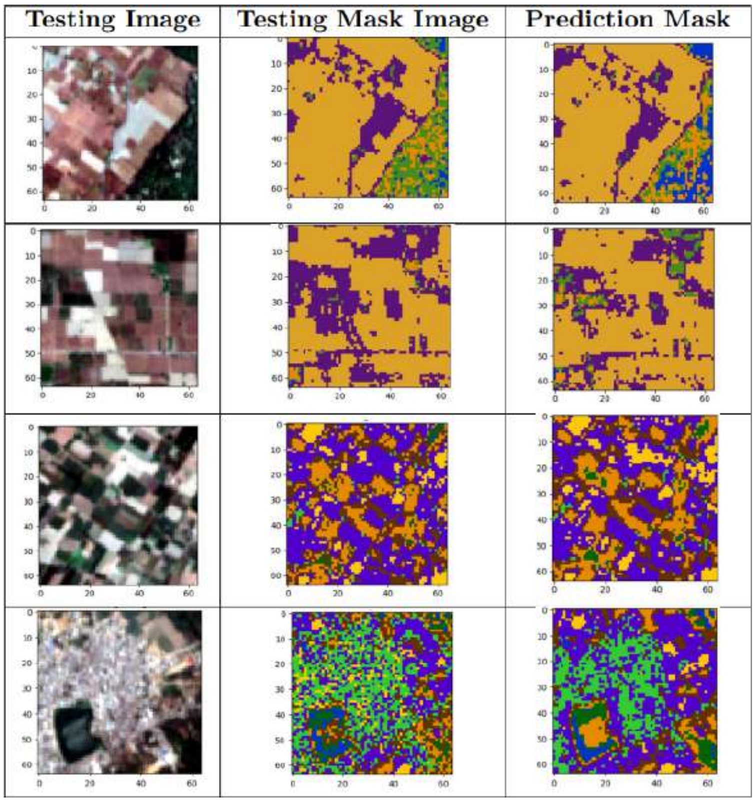

Figure 6.3: Linknet-Inceptionv3 Model: Testing Images and Predicted Masks

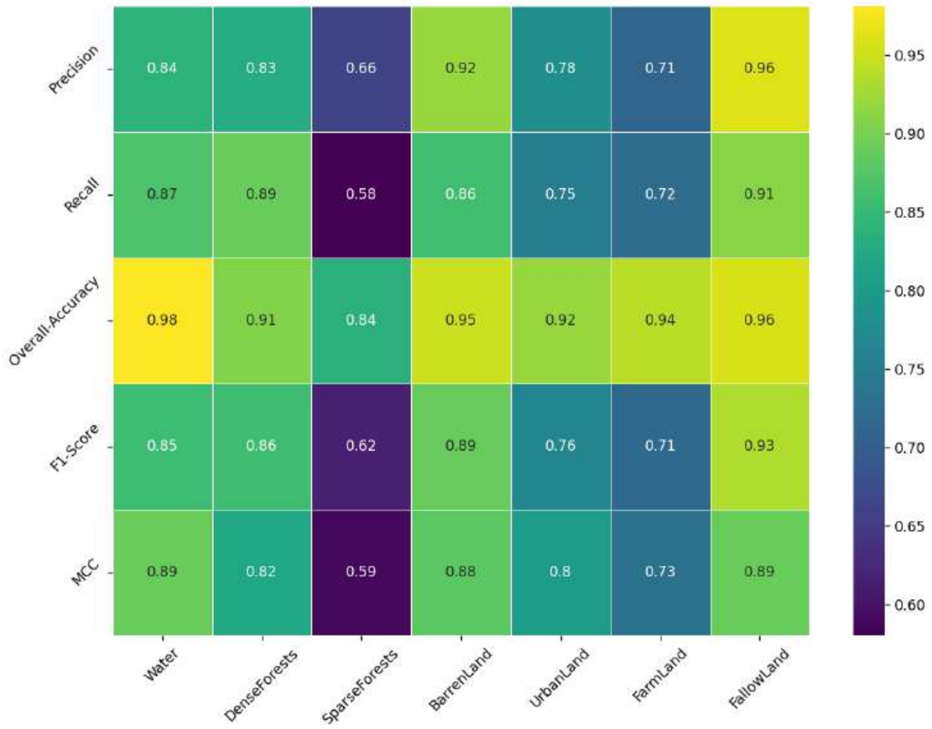

Figure 6.4: Metrics for Unet EfficientNetb7

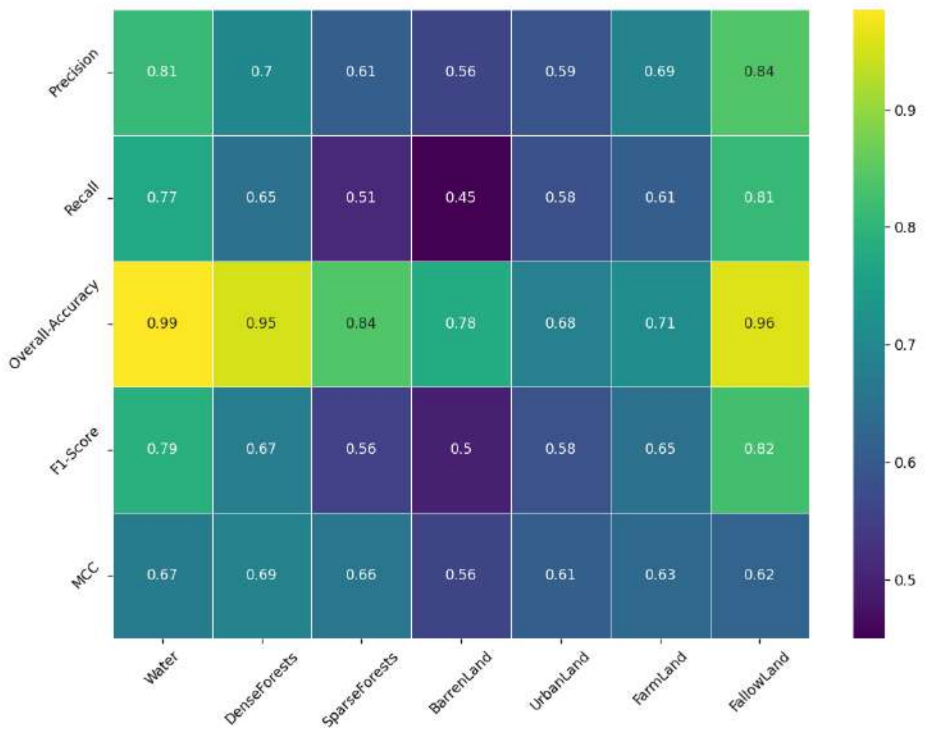

Figure 6.5: Metrics for Linknet Inceptionv3

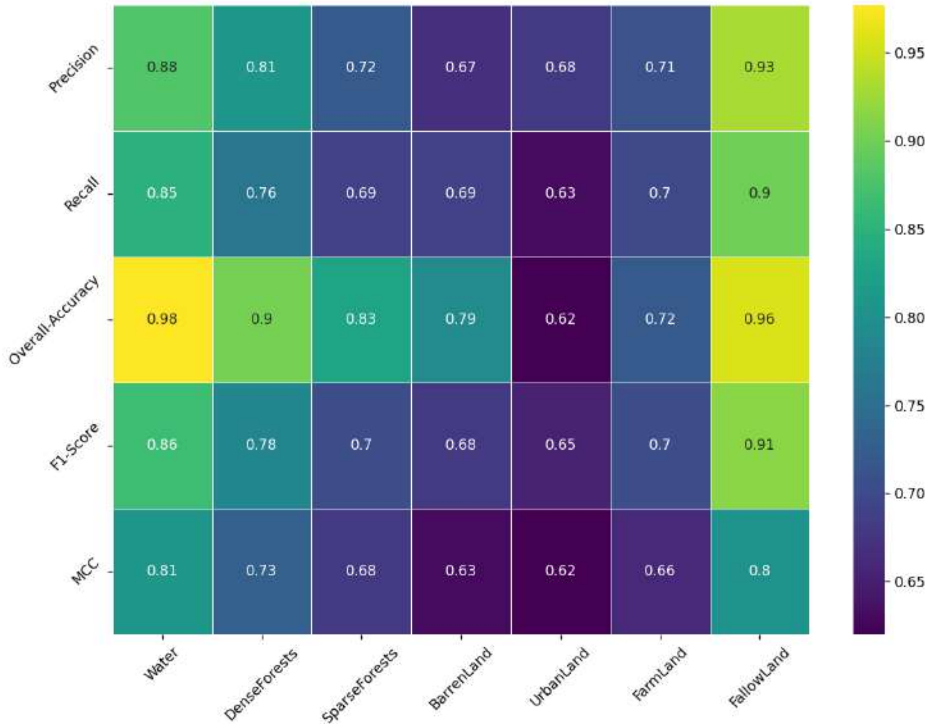

Figure 6.6: Metrics for Unet Inception Resnetv2

Table 6.1: Training and Validation metrics

Sr. No.	**Model**	**Training Accuracy**	**Training Loss**	**Validation Accuracy**	**Validation Loss**
1	Linknet Inceptionv3	0.9432	0.2045	0.9413	0.2167
2	Linknet ResNet152	0.9262	0.2177	0.9234	0.2223
3	Unet DenseNet169	0.9392	0.2197	0.9402	0.2181
4	Unet ResNext101	0.9332	0.2109	0.9292	0.2197
5	Unet Inception Resnetv2	0.9487	0.2001	0.9433	0.2033
6	Unet EfficientNetb7	0.9605	0.1965	0.9563	0.2170

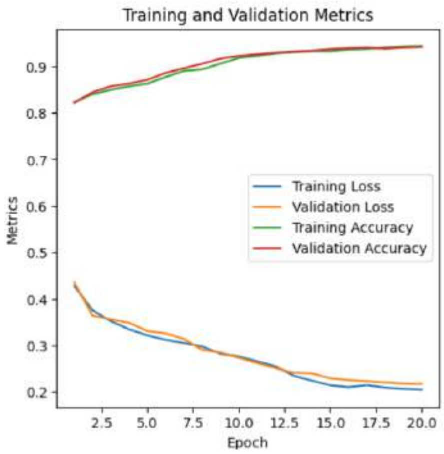

Figure 6.7: Linknet Inceptionv3

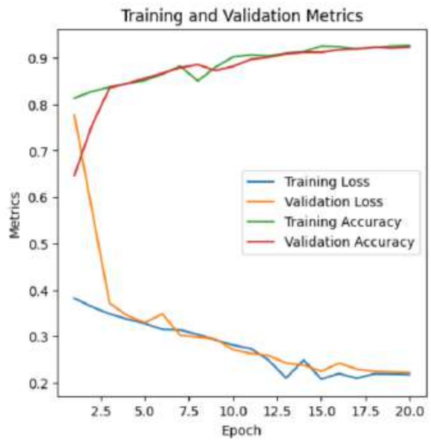

Figure 6.8: Linknet Resnet152

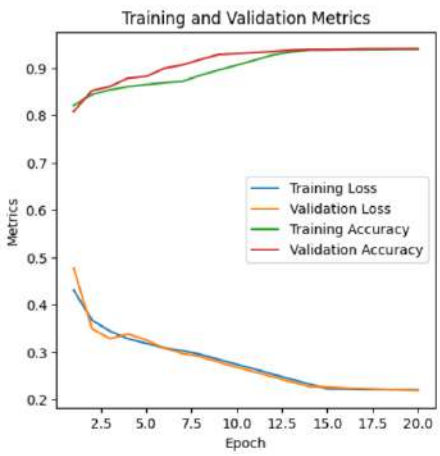

Figure 6.9: Unet Densenet169

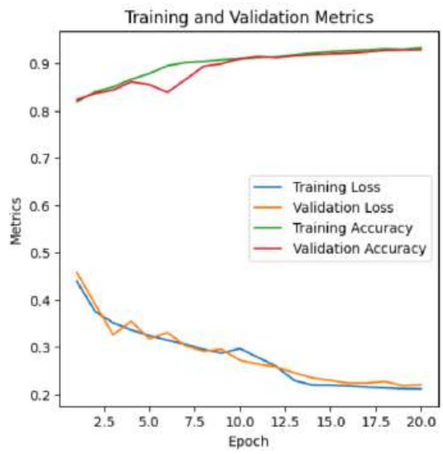

Figure 6.10: Unet Resnext101

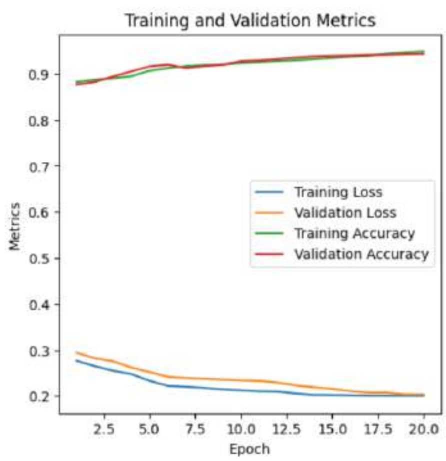

Figure 6.11: Unet Inception Resnetv2

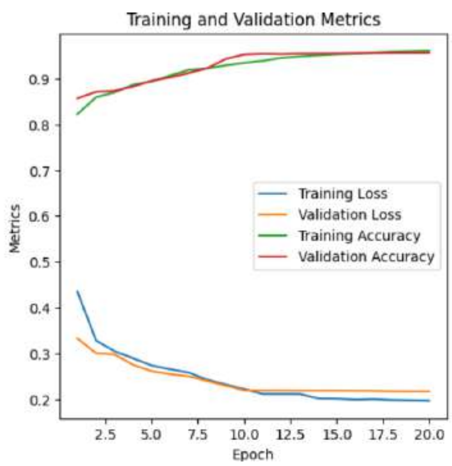

Figure 6.12: Unet Efficientnetb7

The variations in model performance can be attributed to the architectural nuances of each model. While some models might excel in learning complex features, others might prioritize generalization. Ultimately, based on the results, Unet EfficientNetb7 stands out as the most effective model for this specific classification task, offering a balance between training efficiency and robust generalization.

The EfficientNet architecture is known for its efficiency and effectiveness in balancing model size and accuracy. EfficientNet models are designed to achieve better performance while requiring fewer resources compared to other architectures. This efficiency allows EfficientNetB7 to achieve a higher accuracy with fewer parameters, making it a more efficient choice for resource-constrained environments.

Second, EfficientNetB7 is a large-scale model with a high level of complexity, which allows it to capture intricate patterns and features in the dataset. This complexity enables the model to learn more nuanced representations of the data, leading to higher accuracy in classification tasks.

Additionally, EfficientNetB7 benefits from transfer learning, which involves using pre-trained weights from models trained on large-scale datasets. This transfer learning approach helps the model quickly adapt to new tasks and datasets, leading to faster convergence and better performance.

Overall, the combination of efficiency, complexity, and transfer learning makes EfficientNetB7 the best-performing model in this context, achieving the highest accuracy in classifying Land Use Land Cover compared to other models. Using Efficentnetb7 we have classified our study areas into the seven LULC classes as mentioned in Table 5.1. The classified map of Hazira-Ankleshwar and Dadri-Panipat are given below

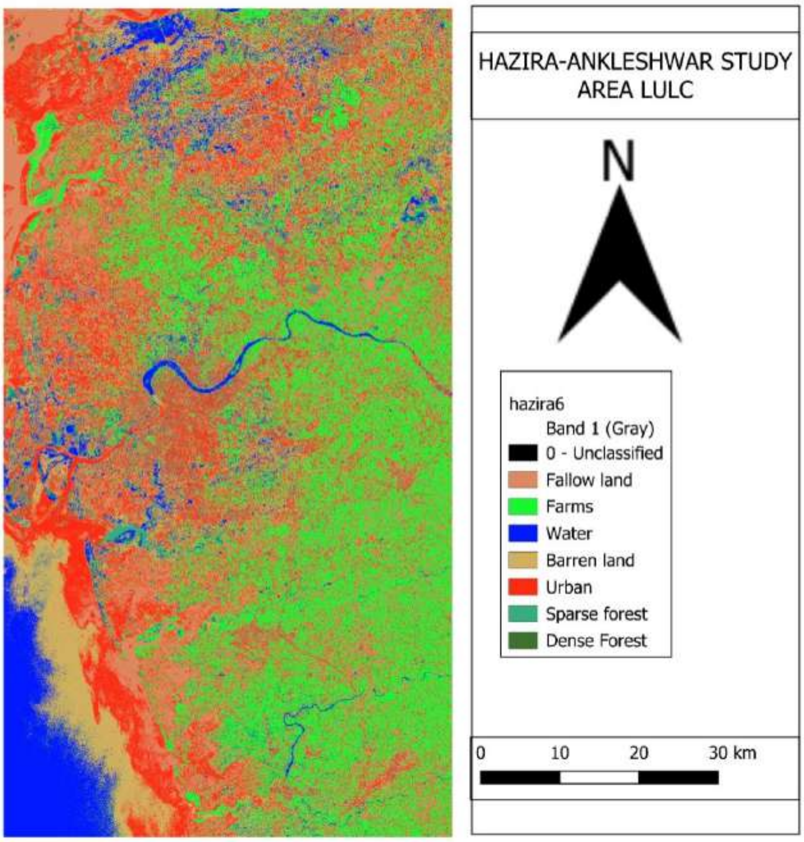

Figure 6.13: Hazira-Ankelshwar study area LULC

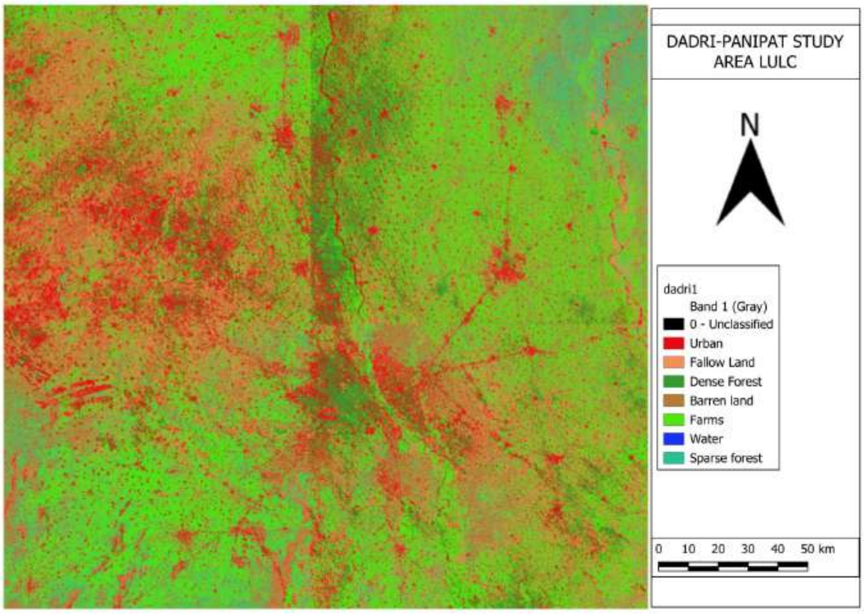

Figure 6.14: Dadri-Panipat study area LULC

6.2 AHP

In the implementation of AHP, pairwise comparisons were conducted to determine the relative importance of seven land use and land cover classes. The obtained normalized weights as shown in Table 6.2 reveal that urban areas hold the highest significance with a weight of 0.2801, followed closely by dense forest at 0.2748. Farms and water bodies also contribute significantly, with weights of 0.2339 and 0.1105, respectively. Barren land, fallow land, and sparse forest exhibit comparatively lower weights, indicating their relatively lesser importance in the context of pipeline route decision-making, with values of 0.0181, 0.0323, and 0.0499, respectively. These weights provide valuable insights into the relative priorities of different land cover classes, aiding in informed decision-making processes.

Table 6.2: AHP weights for Land Cover Classes

Name	**Normalized Weights**
BarrenLand	0.0181
DenseForest	0.2748
FallowLand	0.0323
Farms	0.2339
SparseForest	0.0499
Urban	0.2801
Water	0.1105

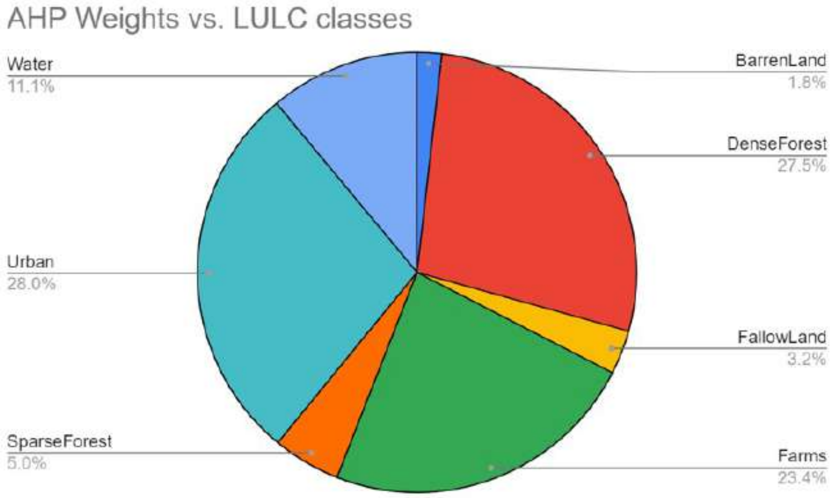

Figure 6.15: AHP weights for Land Cover Classes

6.3 Route Optimization

In the Route Optimization phase, we employed five Least Cost Path Analysis (LCPA) heuristics to guide path finding algorithms towards efficient and optimal routes within a spatial network. Specifically, we implemented heuristics such as A* with Chebyshev Distance, A* with Diagonal Movement, A* with Euclidean Distance, A* with Manhattan Distance, and Dijkstra's Distance. These heuristics were chosen for their effectiveness in identifying the least cost paths for pipeline routes.

To ensure a comprehensive analysis, all identified heuristics were applied to both the Dadri-Panipat and Haizra-Ankleshwar study areas. This allowed us to assess their performance across different land cover classes and compare the results with the original pipeline routes. Through this comparative analysis, we sought to identify the most effective heuristic approach for optimizing pipeline routes, thereby enhancing efficiency and reducing costs in pipeline construction and maintenance.

6.3.1 Dadri-Panipat Study Area

The detailed comparison among the various heuristics is presented in Table 6.4, Table 6.5, Table 6.6, Table 6.7, and Table 6.8. These tables offer a comprehensive breakdown of the optimized pipeline distances, road percentages, road kilometers, and land use/land cover (LULC) pixel distributions for each algorithm applied to the Dadri-Panipat Gas Pipeline route optimization. They provide valuable insights into the performance and distribution characteristics of Dijkstra's Algorithm in comparison to the A* algorithms (Euclidean, Manhattan, Chebyshev, Diagonal) in achieving optimal pipeline routes while considering specific land use priorities and objectives. Additionally, Table 6.3 provides an overview of the original pipeline route for better understanding and context.

In comparing the results of various algorithms applied to optimize the Dadri-Panipat Gas Pipeline route, it's evident that the A* algorithms (Euclidean, Manhattan, Chebyshev, Diagonal) consistently achieved superior efficiency with optimized distances around 147-150 kilometers, significantly reducing the original pipeline length of 200 kilometers. These A* algorithms demonstrated a more balanced distribution of road construction across different land use/land cover (LULC) categories, with road percentages allocated to Urban-land, Sparse-forest, and other areas. Among these, the A* algorithm with Manhattan distance achieved the shortest optimized distance of 143.17 Km as compared to other heuristics.

Among the algorithms, Dijkstra's algorithm performs relatively better in avoiding farms, with only 0.65% of the pipeline passing through farmlands compared to other algorithms.It also exhibits the highest efficiency in avoiding dense forests, with only 0.08% of the pipeline passing through these areas. This is followed closely by A* with Chebyshev distance, which allocates 0.62%

of the pipeline through dense forests. Dijkstra's algorithm also demonstrates superior performance in avoiding urban areas, with only 0.64% of the pipeline passing through residential zones. In contrast, other A* algorithms allocate higher percentages of the pipeline through urban areas, ranging from 19.81% to 27.68%.

Despite Dijkstra's algorithm resulting in a higher optimized distance of 150.44 km compared to other algorithms, it achieves the most optimized route by efficiently allocating the pipeline through barren lands(79.5%) and sparse forests(11.39%) as can be seen in figure 6.17. These land cover classes have a higher proportion of pipeline percentage allocation, while dense forests, water bodies, urban areas, and farms receive negligible pipeline percentages. Therefore, it effectively minimizes the impact on densely populated or environmentally sensitive areas, making it the most optimized choice for the Dadri-Panipat gas pipeline route.

Table 6.3: Dadri-Panipat Gas Pipeline Original Statistics

	Dense-Forest	Sparse-Forest	Farms	Barren	Residential	Water	Fallow	Total
Pixels LULC	0	2	17	4	11	0	3	37 pxs
Pipeline Percentage	0	5.41	45.95	10.81	29.73	0	8.11	100%
Kilometre	0	11.16	94.76	22.29	61.31	0	16.72	206.22 Km

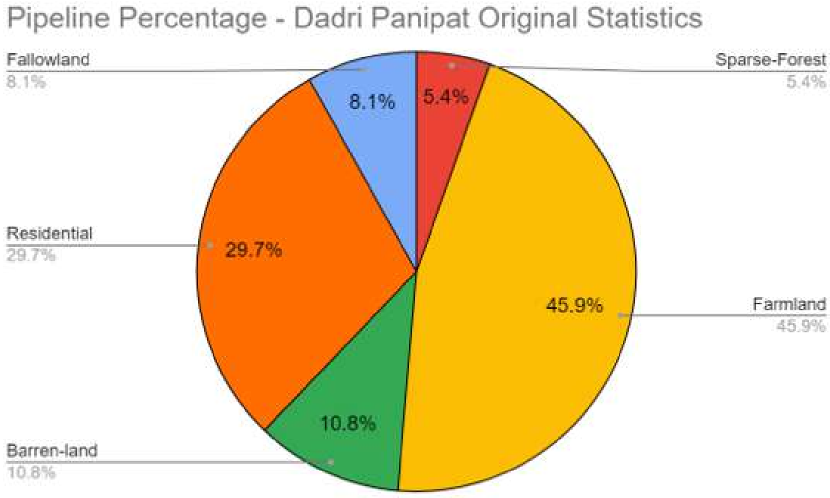

Figure 6.16: Dadri-Panipat Gas Pipeline Original

Table 6.4: Dadri Panipat-Dijkstra's algorithm Route Analysis

	Dense-Forest	Sparse-Forest	Farms	Barren	Residential	Water	Fallow	Total
Pixels LULC	11	1550	88	10814	87	58	995	13603 pxs
Pipeline Percentage	0.08	11.39	0.65	79.5	0.64	0.43	7.31	100.00%
Kilometre	0.12	17.14	0.98	119.6	0.96	0.65	11	150.44 Km

Table 6.5: Dadri Panipat-A* Manhattan distance Route Analysis

	Dense-Forest	Sparse-Forest	Farms	Barren	Residential	Water	Fallow	Total
Pixels LULC	557	696	1628	3333	2560	139	1212	10125 pxs
Pipeline Percentage	5.5	6.87	16.08	32.92	25.28	1.37	11.97	100.00%
Kilometre	7.87	9.84	23.02	47.13	36.19	1.96	17.14	143.17 Km

Table 6.6: Dadri Panipat-A* Euclidean distance Route Analysis

	Dense-Forest	Sparse-Forest	Farms	Barren	Residential	Water	Fallow	Total
Pixels LULC	78	218	969	3554	2881	1480	1227	10407 pxs
Pipeline Percentage	0.75	2.09	9.31	34.15	27.68	14.22	11.79	100.00%
Kilometre	1.1	3.08	13.7	50.26	40.73	20.93	17.35	147.16 Km

Table 6.7: Dadri Panipat-A* Diagonal distance Route Analysis

	Dense-Forest	Sparse-Forest	Farms	Barren	Residential	Water	Fallow	Total
Pixels LULC	217	952	1576	3560	2820	84	1189	10398 pxs
Pipeline Percentage	2.09	9.16	15.16	34.24	27.12	0.81	11.43	100.00%
Kilometre	3.07	13.47	22.29	50.35	39.88	1.19	16.81	147.04 Km

Table 6.8: Dadri Panipat-A* Chebyshev distance Route Analysis

	Dense-Forest	Sparse-Forest	Farms	Barren	Residential	Water	Fallow	Total
Pixels LULC	66	1770	1873	3761	2108	239	822	10639 pxs
Pipeline Percentage	0.62	16.64	17.61	35.35	19.81	2.25	7.73	100.00%
Kilometre	0.93	25.03	26.49	53.18	29.8	3.38	11.63	150.44 Km

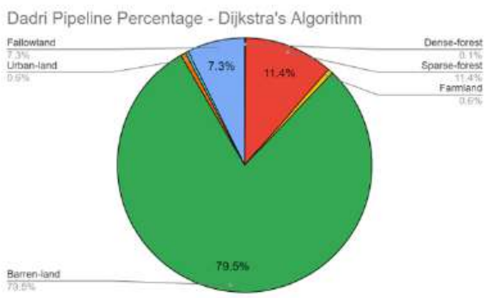

Figure 6.17: Dadri-Dijkstra's algorithm

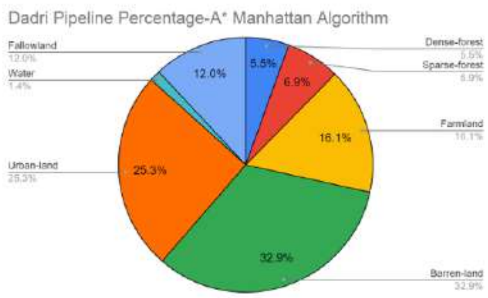

Figure 6.18: Dadri-A* Manhattan

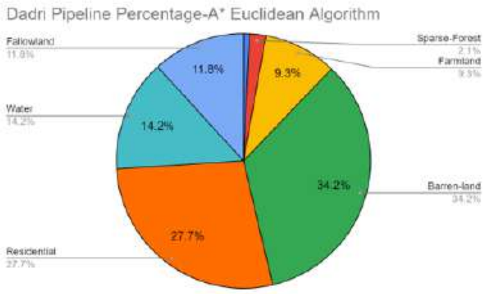

Figure 6.19: Dadri-A* Euclidean

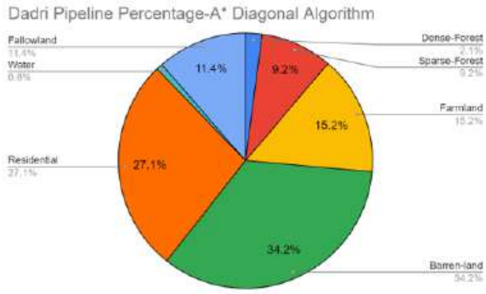

Figure 6.20: Dadri-A* Diagonal

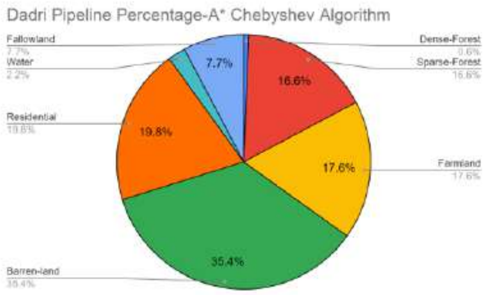

Figure 6.21: Dadri-A* Chebyshev

6.3.2 Hazira-Ankleshwar Study Area

The detailed results of the comparison between algorithms can be observed in Table 6.10, Table 6.11, Table 6.12 , Table 6.13, and Table 6.14, which provide a comprehensive breakdown of the optimized pipeline distances, road percentages, road kilometers, and land use/land cover (LULC) pixel distributions for each algorithm applied to the Hazira-Ankleshwar Gas Pipeline route optimization. These tables offer valuable insights into the performance and distribution characteristics of Dijkstra's Algorithm compared to the A* algorithms (Euclidean, Manhattan, Chebyshev, Diagonal) in achieving optimal pipeline routes while considering specific land use priorities and objectives. Table 6.9 gives an understanding of the original pipeline route.

In comparing the results of various algorithms applied to optimize the Hazira-Ankleshwar Gas Pipeline route, it's evident that the A* algorithms

(Euclidean, Manhattan, Chebyshev, Diagonal) consistently achieved superior efficiency with optimized distances around 55 kilometers, significantly reducing the original pipeline length of 90 kilometers. These A* algorithms demonstrated a more balanced distribution of road construction across different land use/land cover (LULC) categories, with road percentages allocated to Urban-land, Sparse-forest, and other areas.

However, it's worth noting that Dijkstra's Algorithm, despite resulting in a slightly longer optimized distance of 77.65 kilometers, exhibited a more concentrated distribution of road development primarily in Barren-land (91.85%) as shown in figure 6.23. This focused distribution aligns with our project's aim of minimizing pipeline development in specific areas such as Urban-land, Water, Farms, Dense forest, and Sparse forest, while prioritizing routes through fallow land and Sparse-forest.

Overall, while the A* algorithms demonstrated superior optimization in terms of distance reduction, Dijkstra's Algorithm showed a more targeted approach in minimizing road development across critical land use categories. The choice of algorithm ultimately depends on the specific project goals and objectives, balancing optimization with the strategic distribution of pipeline routes to align with environmental and land use considerations.

Table 6.9: Hazira-Ankleshwar Gas Pipeline Original Statistics

	Dense-Forest	Sparse-Forest	Farms	Barren	Residential	Water	Fallow	Total
Pixels LULC	3	7	3	11	9	1	0	34 pxs
Pipeline Percentage	8.82	20.59	8.82	32.35	26.47	2.94	0	100%
Kilometre	7.93	18.53	7.93	29.11	23.86	2.64	0	90 Km

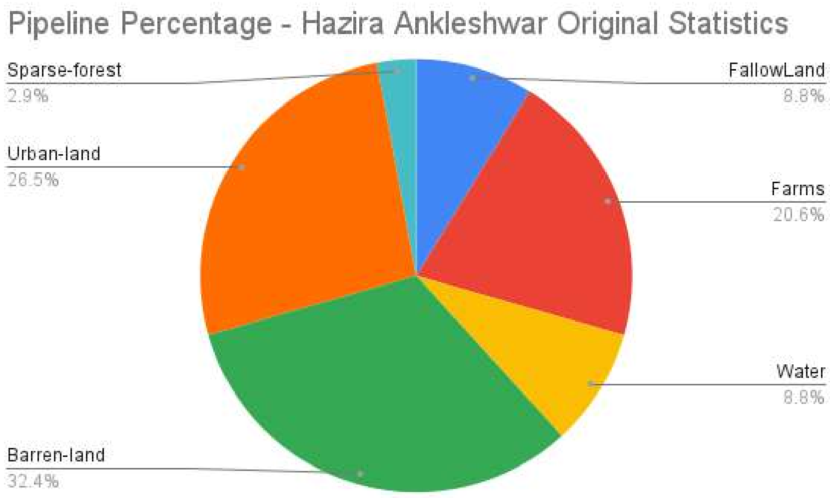

Figure 6.22: Hazira-Ankleshwar Gas Pipeline Original

Table 6.10: Hazira Ankleshwar-Dijkstra's algorithm Route Analysis

	Dense-Forest	Sparse-Forest	Farms	Barren	Residential	Water	Fallow	Total
Pixels LULC	63	32	70	7133	24	444	0	7766 pxs
Pipeline Percentage	0.81	0.41	0.9	91.85	0.31	5.72	0	100.00%
Kilometre	0.63	0.32	0.7	71.32	0.24	4.44	0	77.65 Km

Table 6.11: Hazira Ankleshwar-A* Manhattan distance Route Analysis

	Dense-Forest	Sparse-Forest	Farms	Barren	Residential	Water	Fallow	Total
Pixels LULC	841	556	465	1854	1692	166	2	5576 pxs
Pipeline Percentage	15.08	9.97	8.34	33.25	30.34	2.98	0.04	100.00%
Kilometre	8.41	5.56	4.65	18.54	16.91	1.66	0.02	55.75 Km

Table 6.12: Hazira Ankleshwar-A* Euclidean distance Route Analysis

	Dense-Forest	Sparse-Forest	Farms	Barren	Residential	Water	Fallow	Total
Pixels LULC	741	618	463	1873	1655	160	3	5513 pxs
Pipeline Percentage	13.44	11.21	8.4	33.91	30.02	2.9	0.05	100.00%
Kilometre	7.41	6.18	4.63	18.72	16.55	1.6	0.03	55.12 Km

Table 6.13: Hazira Ankleshwar-A* Diagonal distance Route Analysis

	Dense-Forest	Sparse-Forest	Farms	Barren	Residential	Water	Fallow	Total
Pixels LULC	739	649	488	1879	1644	176	2	5577 pxs
Pipeline Percentage	13.25	11.64	8.75	33.69	29.48	3.16	0.04	100.00%
Kilometre	7.39	6.49	4.88	18.79	16.44	1.76	0.02	55.76 Km

Table 6.14: Hazira Ankleshwar-A* Chebyshev distance Route Analysis

	Dense-Forest	Sparse-Forest	Farms	Barren	Residential	Water	Fallow	Total
Pixels LULC	745	643	512	1852	1653	164	1	5570 pxs
Pipeline Percentage	13.38	11.54	9.19	33.25	29.68	2.94	0.02	100.00%
Kilometre	7.45	6.43	5.12	18.52	16.53	1.64	0.01	55.69 Km

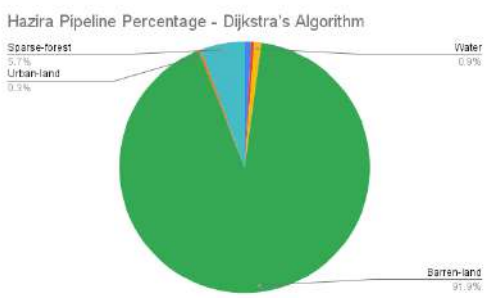

Figure 6.23: Hazira-Dijkstra's algorithm

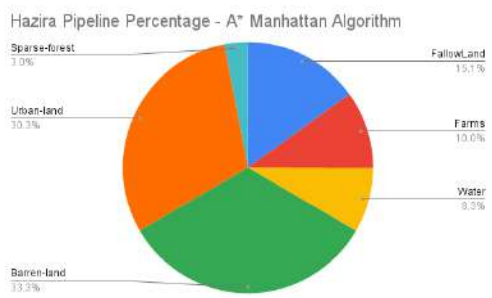

Figure 6.24: Hazira-A* Manhattan

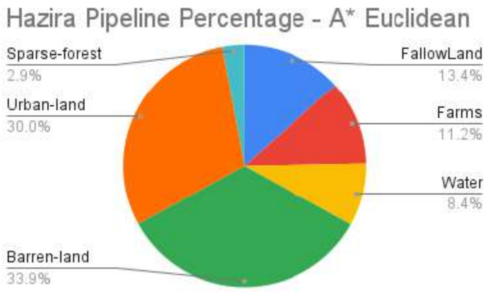

Figure 6.25: Hazira-A* Euclidean

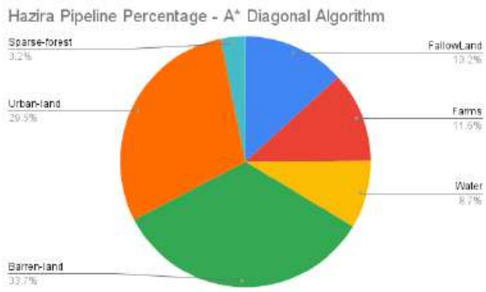

Figure 6.26: Hazira-A* Diagonal

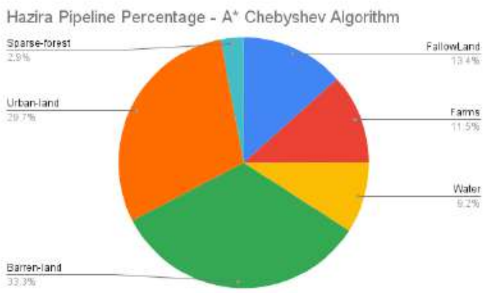

Figure 6.27: Hazira-A* Chebyshev

Chapter 7

Conclusion

In this research, we delved into the complexities of creating a smart pipeline route optimization system. We began by examining the current state of pipeline infrastructure planning, highlighting the industry's focus on sustainability, cost-effectiveness, and technological progress. We critiqued traditional pipeline construction methods for their shortcomings, particularly in neglecting the nuanced interaction of technical, environmental, and safety factors, resulting in sub-optimal routes and heightened risks.

The methodological approach focuses on the necessity for a cost-effective and environmentally friendly pipeline route optimization technique. The integration of GIS, RS technologies, machine learning models, and MCDM methodologies emerges as a promising solution. The ultimate aim is to design a system that not only considers cost-effectiveness but also minimizes the environmental impact of pipeline construction.

The methodological execution unfolds in a systematic manner. The initial phase involved the meticulous downloading of satellite imagery and selecting suitable satellite imagery sources. Data pre-processing was undertaken to create an organized and verified dataset serving as the foundational element for intelligent pipeline route optimization analysis.

A significant portion of the methodology was dedicated to LULC classification tailored for the Indian region divided into seven land cover classes. In the integration of Deep Learning (DL) models, including architectures like Linknet Inceptionv3, Linknet ResNet152, Unet DenseNet169, Unet ResNext101, Unet Inception Resnetv2, and Unet EfficientNetb7, for LULC analysis. Each model was carefully selected or designed based on its strengths and characteristics, showcasing the versatility and adaptability of these models for different tasks.

The experimental setup included the "Sen-2 LULC Dataset," and the models were trained on Kaggle's platform, utilizing free GPU resources for efficient computations. The training and validation metrics for each model were presented, with Unet EfficientNetb7 emerging as the best-performing model, exhibiting the highest training accuracy, lowest losses, and strong validation accuracy.

Further steps involved using Multi-Criteria Decision-Making and implementation of the Analytic Hierarchy Process (AHP) to prioritize route selection factors systematically, quantifying their importance and reducing the impact of subjective biases. Subsequently, various AI heuristics, including Dijkstra's Algorithm and different variants of the A* algorithm, were employed for route optimization, going beyond traditional methods, aiming to minimize pipeline length while considering land use/land cover (LULC) priorities.

In the implementation of the Analytic Hierarchy Process (AHP), the relative importance of seven land use and land cover classes was determined through pairwise comparisons. Urban areas emerged as the most significant, followed closely by dense forests, farms, and water bodies, indicating their crucial role in pipeline route decision-making. Despite Dijkstra's Algorithm resulting in a slightly longer optimized distance compared to other algorithms, it efficiently allocated the pipeline through barren lands and sparse forests, achieving the most optimized route.

In both the Dadri-Panipat and Hazira-Ankleshwar study areas, Dijkstra's Algorithm demonstrated a more targeted approach to minimizing development across critical land use categories, such as dense forests and urban lands. For the Dadri-Panipat study area, the original pipeline length was approximately 206.22 kilometers, while the optimized distance ranged from 143.17 to 150.44 kilometers, showcasing notable reductions in pipeline length. Similarly, in the Hazira-Ankleshwar study area, the original pipeline route spanned approximately 90 kilometers, whereas the optimized distances ranged from around 55 to 77.65 kilometers. While the A* algorithms excelled in distance reduction, the choice of algorithm ultimately depends on project goals, balancing optimization with strategic considerations for environmental and land use factors.

In summary, this study successfully integrated various technologies and methodologies to develop an intelligent approach for pipeline optimization. The findings underscore the significance of adopting an interdisciplinary approach. Ultimately, the study paves the way for the adoption of intelligent approaches in pipeline optimization, facilitating sustainable and environmentally conscious infrastructure development. This report not only summarizes the current state of pipeline route optimization but also sets the stage for future improvements, ensuring progress in sustainable, cost-effective, and technologically advanced solutions for pipeline planning.

Chapter 8

Publication Details

1. **Springer Chapter Submission**

   Paper Title: "Deep Learning Enhanced LULC Classification"

   Book Series: "Advances in Geographic Information Science"

   Book title: "Application of Geospatial Technology and Modelling on Natural Resources Management - Current State, Challenges and Sustainability"

   Chapter 13: "Geospatial Techniques for Mapping and Monitoring Land Use and Land Cover (LULC)"

   Status: Accepted on 24th April, 2024

Re: Submission of Draft for Chapter 13: "Geospatial Techniques for Mapping and Monitoring LULC"

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Wed 4/24/2024 9:39 AM
To:MIHIKA RIYA SANGHVI <mihikars20.comp@coeptech.ac.in>
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Dear author,

The abstract is accepted.
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Plagiarism should be less than 15%.

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Editorial Team

2. **IEEE Conference Submission**

   Paper Title: ”Leveraging Artificial Intelligence for Strategic Pipeline Routing in India”

   Conference: ”IEEE 2nd World Conference on Communication and Computing”

   Status: Submitted on 14th May, 2024

Bibliography

[1] Cihan Akyel and Nursal Arıcı. Linknet-b7: Noise removal and lesion segmentation in images of skin cancer. *Mathematics*, 10:736, 02 2022.

[2] Luqman Ali, Fady Alnajjar, Hamad Jassmi, Munkhjargal Gochoo, Wasif Khan, and Mohamed Serhani. Performance evaluation of deep cnn-based crack detection and localization techniques for concrete structures. *Sensors*, 21:1688, 03 2021.

[3] Karadavut S. Aydin, C.C. The impact of the increasing use of natural gas on the environment and population in ankara, turkey. *Fresenius Environ. Bull*, 2010.

[4] Daniel Baeza, Christian F Ihle, and Julián M Ortiz. A comparison between aco and dijkstra algorithms for optimal ore concentrate pipeline routing. *Journal of Cleaner Production*, 144:149–160, 2017.

[5] Abdul-Lateef Balogun, Abdul-Nasir Matori, Adekunle Isa Hamid-Mosaku, Dano Umar Lawal, and Imtiaz Ahmed Chandio. Fuzzy mcdm-based gis model for subsea oil pipeline route optimization: An integrated approach. *Marine Georesources & Geotechnology*, 35(7):961–969, 2017.

[6] Rodrigo Ribeiro de Lucena, Juliana Souza Baioco, Beatriz Souza Leite Pires de Lima, Carl Horst Albrecht, and Breno Pinheiro Jacob. Optimal design of submarine pipeline routes by genetic algorithm with

different constraint handling techniques. *Advances in Engineering Software*, 76:110–124, 2014.

[7] Ali Ihsan Durmaz, Erdinç Örsan Ünal, and Cevdet Coşkun Aydın. Automatic pipeline route design with multi-criteria evaluation based on least-cost path analysis and line-based cartographic simplification: A case study of the mus project in turkey. *ISPRS international journal of geo-information*, 8(4):173, 2019.

[8] Sandra C. Feldman, Ramona E. Pelletier, Ed Walser, James C. Smoot, and Douglas Ahl. A prototype for pipeline routing using remotely sensed data and geographic information system analysis. *Remote Sensing of Environment*, 53(2):123–131, 1995. Geologic Remote Sensing.

[9] Gunawan Gunawan, Allessandro Setyo Anggito Utomo, and Altabibi Naufal Syafaq. Piping system development in oil and gas field based on dijkstra's algorithm and genetic algorithm. In *AIP Conference Proceedings*, volume 2376. AIP Publishing, 2021.

[10] Bernard Amponfi Gyabeng and A Bernard. Selection of optimum petroleum pipeline routes using a multi-criteria decision analysis and gis least-cost path approach. *International Journal of Scientific and Research Publications (IJSRP)*, 10(06):572–579, 2020.

[11] Isa Adekunle Hamid-Mosaku, Olatoye Fatai Oguntade, Victoria Ifeoma Ifeanyi, Abdul-Lateef Balogun, and Olalekan Abeeb Jimoh. Evolving a comprehensive geomatics multi-criteria evaluation index model for optimal pipeline route selection. *Structure and Infrastructure Engineering*, 16, 2020.

[12] Piotr Jankowski and L Richard. Integration of gis-based suitability analysis and multicriteria evaluation in a spatial decision support system for route selection. *Environment and Planning B: Planning and Design*, 21:323–340, 05 1994.

[13] Ju Young Kang and Byung Suk Lee. Optimisation of pipeline route in the presence of obstacles based on a least cost path algorithm and laplacian smoothing. *International Journal of Naval Architecture and Ocean Engineering*, 9(5):492–498, 2017.

[14] Jason Luettinger and Thayne Clark. Geographic information system-based pipeline route selection process. *Journal of Water Resources Planning and Management-asce - J WATER RESOUR PLAN MAN-ASCE*, 131, 05 2005.

[15] Junjun Ma, Zhaohong Xu, Ergong Zheng, and Qiongjian Fan. Accurate road segmentation in remote sensing images using dense residual learning and improved focal loss. *Journal of Physics: Conference Series*, 1544:012101, 05 2020.

[16] Effie Marcoulaki, I.A. Papazoglou, and Nathalie Pixopoulou. Integrated framework for the design of pipeline systems using stochastic optimisation and gis tools. *Chemical Engineering Research and Design*, 90, 12 2012.

[17] Pedro Moreno-Bernal and Sergio Nesmachnow. A* algorithm for gis-based pipeline route selection in veracruz, mexico. pages 59–64, 2020.

[18] Liu Y. Yuan X Peng, C. Research of image recognition method based on enhanced inception-resnet-v2. *Multimedia Tools and Applications*, 2022.

[19] Denis Pustokhin, Irina Pustokhina, Phuoc Dinh, Son Phan, Nguyen Nhu, Gyanendra Prasad Joshi, and Kripa Shankar. An effective deep residual network based class attention layer with bidirectional lstm for diagnosis and classification of covid-19. *Journal of Applied Statistics*, 50:1–18, 11 2020.

[20] Thomas L Saaty. Decision making with the analytic hierarchy process. *International journal of services sciences*, 1(1):83–98, 2008.

[21] Ahmad Salah and Denis Atwood. Pipeline alignment optimization: Automated gis-based approach. *Journal of Pipeline Systems Engineering and Practice*, 2:2–13, 02 2011.

[22] Rahul Dev; Meshram Vishal; Mistry Shrayank Sawant, Suraj; Garg. Sen-2 lulc. *Mendeley Data*, 2023.

[23] SANI Suleiman, VC Agarwal, DEEPAK Lal, and AMINUDDEEN Sunusi. Optimal route location by least cost path (lcp) analysis using (gis) a case study. *International Journal of Scientific Engineering and Technology Research*, 4(44):9621–9626, 2015.

[24] George Triebel and Todd Crouthamel. Route selection based on a weighted ranking analysis. pages 258–266, 2019.

[25] Jianhua Wan, Guanghui Qi, Zhe Zeng, and Shujuan Sun. The application of ahp in oil and gas pipeline route selection. pages 1–4, 2011.

[26] Zhu Xiaoge and Dong Wentong. Gis technology and application on oil-gas pipeline construction. In *2001 International Conferences on Info-Tech and Info-Net. Proceedings (Cat. No.01EX479)*, volume 1, pages 249–253 vol.1, 2001.

[27] Linlin Zhao, Zhansheng Liu, and Jasper Mbachu. An integrated bim–gis method for planning of water distribution system. *ISPRS International Journal of Geo-Information*, 8(8):331, 2019.