

# Review of Advanced Techniques for Efficient Irrigation Pipeline Routing

Rajesh Kumar V<sup>1,2\*</sup>, Sathiyarayanan S<sup>3</sup>, Hussain Babu D<sup>4</sup> and Guganesh S<sup>5</sup>

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DSc Research Scholar, Manipur International University, India<sup>2</sup>

rajeeii@yahoo.com\*

**Abstract:** This review explores the crucial role of efficient irrigation systems in addressing water scarcity. It highlights the limitations of traditional canal networks and proposes piped irrigation networks as a superior alternative due to their enhanced water use efficiency. The passage then delves into various methodologies for optimal irrigation pipeline route planning and design, emphasizing the use of Geographic Information Systems (GIS) and least cost path analysis. The paper explores the application of least cost path analysis, leveraging Geographic Information Systems (GIS) technology. This method factors in diverse aspects like topography, soil properties, and spatial constraints, leading to the identification of the most economical route for pipeline installation. Furthermore, the potential of image classification using satellite imagery is discussed. By categorizing land cover features such as vegetation and buildings, this technique provides valuable insights for informed decision-making during pipeline route planning. Additionally, the paper investigates the potential of machine learning techniques like spatial clustering. This approach allows for the grouping of similar areas based on various factors, further aiding in the optimization of pipeline routes. By showcasing the cost-saving benefits of these advanced techniques compared to traditional methods, the study emphasizes their significance in achieving sustainable water management practices.

**Keywords:** Pipeline Distribution Network (PDN), Geographic Information Systems (GIS), Least Cost Path (LCP), Image Classification, Spatial Clustering, Genetic Algorithm.

## I. INTRODUCTION

Throughout history, canal networks have served as the primary means of delivering water for irrigation purposes. These systems, typically emanating from rivers, dams, and reservoirs, utilize gravity to transport water through open channels to agricultural fields. However, their reliance on open conveyance methods leads to inherent limitations in water use efficiency, with losses reaching up to 65% during conveyance and distribution. With increasing water scarcity becoming a pressing issue in many regions, the inefficiency of traditional canal irrigation poses a significant challenge. The limited water resources available necessitate the adoption of solutions that minimize losses and ensure optimal usage. Piped irrigation networks present a promising alternative to traditional canal systems. These closed systems utilize pipes to transport water, drastically reducing losses due to evaporation and seepage. Studies indicate that piped networks offer superior water use efficiency, representing a significant improvement over canal systems.

The pipeline system, which contributes significantly to the project's overall cost, oversees moving water from the source to the fields in an irrigation project. An irrigation project's pipeline scope typically accounts for 70–80% of the overall project cost, making it a crucial aspect of project design. Further, considering the pipeline route alignment requires consideration of several variables, such as topography, soil properties, crop requirements, spatial constraints, and irrigation technology, it is equally significant. The efficiency of the irrigation system can be greatly increased, hydraulic losses and energy consumption related to water delivery can be decreased, and in the end, the pipeline routing system can help ensure the sustainable use of water resources and agricultural output.

Determination of the shortest, most uninterrupted, and efficient route is a primary objective in pipe route planning. Planning and design of irrigation network system starts with elaborate survey and collection of data to map all major details i.e., contour/elevation, buildings, roads, rail tracks, lakes, ponds, irrigation structures (Central Water Commission, 2020). In recent times, the application of least cost path analysis to automatically route a pipeline has advanced using Geographic Information Systems (GIS) to the probing stage. a. Geographic Information Systems (GIS) seamlessly merge spatial components with corresponding attributes, enabling a comprehensive and dynamic comprehension of real-world situations. (Rajesh Kumar et al, 2023) The least cost path algorithm is a well-established technique that determines the optimal path between two points based on the lowest resistance to movement.

It can calculate the most convenient route yet avoiding topological and geographical barriers and determining appropriate locations based on their weight. GIS-based least-cost path (LCP) models extend traditional LCP approaches by offering decision-makers a broader spectrum of solutions. This capability stems from the ability to incorporate decision-maker preferences. (Song et al., 2021).

To know and understand the current advancements in GIS and their applications to pipeline projects, a detailed review of literature has been carried out. The review has been structured under four methods/topics: i) Lift irrigation Pipeline routing ii) Image Classification, iii) Clustering by Machine Learning and iv) Least cost path method.

## II. IRRIGATION PIPELINE ROUTING

Considering the scarcity of water, the Pipeline Distribution Network (PDN) system is recommended for irrigation. As pipeline networks are buried under the soil, land acquisition cost is reduced, losses due to evaporation, theft can be avoided (Sandesh and Valunjkar, 2017). The guidelines for planning and design of piped irrigation network, CWC (2017) states that the pipe route of minimal length will have effective utilization of water and economical design. Figure 1 shows the typical pipeline irrigation network.

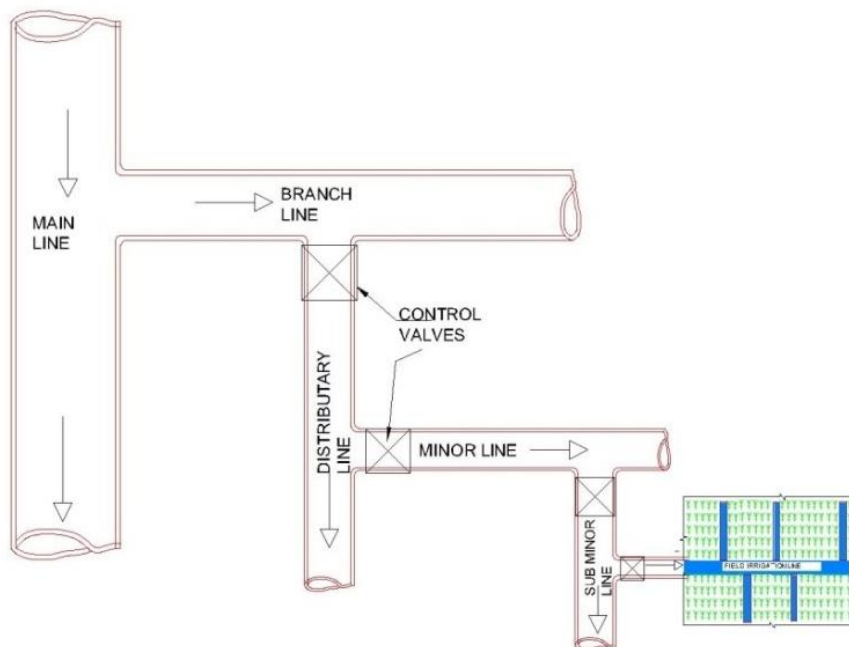


Figure 1: Typical Pipeline Irrigation Network

(Source: Guidelines for planning and design of piped irrigation network, CWC)

The requirement of irrigation efficiency will increase to 60% soon as the availability of fresh water is in crisis. Thus, a well-planned PDN can be operated with a efficiency of 70 to 80 % compare to Canal Distribution Network with efficiency ranges from 20 to 35 %. (Kolhe P, 2012).

Most of the optimization techniques involve several input parameters and it is very important to achieve reasonable results. More parameters require extensive trials and tuning, which is time consuming, to evaluate the optimum results. (Gajghate & Mirajkar, 2021).

## III. IMAGE CLASSIFICATION

The task of classifying all the pixels in a remotely sensed image is known as image classification. It could be Unsupervised and supervised classification. Providing information on which categories to assign various pixels or segments is called supervised classification. Unsupervised categorization considers both neighbouring pixels and spatial data. They both can be either pixel-based or object-based.

The classic method for determining which class each pixel belongs in is pixel-based classification. It disregards any data from nearby pixels, resulting in a "salt and pepper" effect. The object-based approach groups pixels together based on their similarity and considers the colour and shape features of neighbouring pixels when grouping. (ESRI, 2021)

Object-based Image Analysis (OBIA) is a method of image analysis that differs from the traditional pixel-based method. OBIA employs a novel method of picture analysis that considers the importance of spatial and dynamic factors like texture, context, and shape. (Hay and Castilla, 2006). Because an object is a collection of pixels, object attributes such as mean value, standard deviation, ratio, and so on may be determined; additionally, shape and texture features of the objects can be utilized to distinguish land cover classes with comparable spectral data. OBIA can build land cover thematic maps with higher accuracy than standard pixel-based methods. (Gao & Mas, 2006)

ANNs were created to emulate the human brain's neural storage and analysis functions. ANN methods offer a particular advantage over statistical classification methods in that they are non-parametric and require little or no prior knowledge of the input data distribution model. Parallel computing, the ability to estimate the non-linear relationship between input data and desired outputs, and the ability to generalise quickly are all additional advantages of ANNs. ANNs outperform classical classification approaches like maximum likelihood classifiers, Support Vector Machine classifiers, random forest and Decision tree algorithm in terms of classification accuracy. (Benediktsson et al., 1990; Benediktsson & Sveinsson, 1997)

Convolutional neural networks, long short-term memory recurrent neural networks, and gated recurrent unit RNNs have all been proven to extract temporal data efficiently for classification tasks. Sentinel-1A (S1A) imagery with a 12-day return time and a high spatial resolution of roughly 10 m has recently become available, making it possible to fully exploit phenological data to improve early crop classification. To circumvent the necessity for ideal designs and hyper-parameters, an incremental classification technique was added. First, the complete image time series was trained to 1D CNNs, LSTM RNNs, and GRU RNN 'classifiers,' resulting in three classifiers with optimal designs. Among the three classifiers, CNNs had the highest Kappa coefficient (0.942). (Zhao et al., 2019)

Olaf Ronneberger et al. created the UNET type CNN for Bio Medical Image Segmentation. It's an end-to-end fully convolutional network, which means it only has convolutional layers and no dense layers, allowing it to handle images of any size. The architecture includes two approaches for exact localisation utilising transposed convolutions: the contraction path and the symmetric expanding path. A schematic representation of UNET is depicted in figure 2.

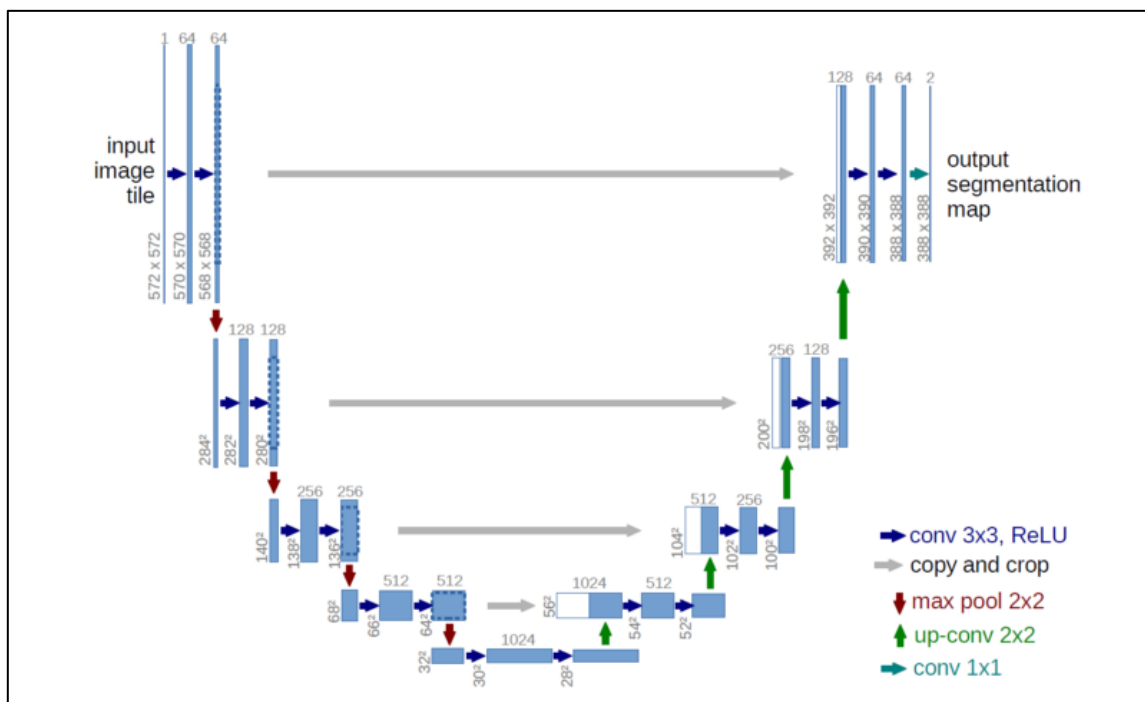


Figure 2: UNET Architecture

Although the U-net is now one of the most popular deep learning algorithms for mapping land use/land cover (LULC), it has only been employed with synthetic aperture radar (SAR) and multispectral (MS) images on a few occasions. On the other hand, because of their variations in biodiversity and ecosystem services provision, the distinction between plantations and forests in LULC maps has been emphasized, particularly in tropical locations. In this study, a U-net model is trained with different imaging inputs from Sentinel-1 and Sentinel-2 satellites, MS, SAR, and a combination of both (MS + SAR), as well as a random forests algorithm (RF) with the MS + SAR input. The MS + SAR U-net produced the most accurate findings, with a 0.76 overall accuracy and a 0.58 average F1-score. The addition of the SAR band resulted in an F1-score increment of 0.08–0.11. The MS + SAR U-net consistently outperformed the MS + SAR RF in nearly every class. The findings suggest that combining SAR and MS pictures into a U-net enabled a greater F1-score and accuracy. (Solorzano et.al.,2021)

Land usage (LU) maps, unlike land categorization maps, are difficult to generate automatically. Deep learning is a cutting-edge methodology for quickly creating LU maps. However, because the deep learning output is dependent on the training input. Using data on the number of building floors retrieved from a digital topographic map and 51 cm resolution aerial orthoimages as inputs, a method for securing correct LU information is developed and used for ground truthing. A Conv-Depth Block (CDB) ResU-Net architecture was proposed and applied to three complicated metropolitan areas in Korea with diverse LU characteristics to evaluate the adaptability of the network. For the test samples, the suggested CDB ResU-Net attained an overall accuracy of 83.7 percent. In identifying residential classes, the network outperformed Deeplab v3+, ResUnet, ResASPP-Unet, and context-based ResU-Net. (Suhong et.al., 2022)

#### **IV. SPATIAL CLUSTERING**

The world's most difficult questions are multifaceted and nuanced. This is recognised by effective data-driven learning strategies. Many questions and challenges are multidimensional by nature; they are influenced, shaped, and characterised by a variety of factors all acting at the same time. Multivariate processes, as opposed to univariate processes, in which only one variable acts at the same time, are statistical concepts. Clustering is a basic spatial analysis technique for extracting information from big, complicated multivariate processes. It works by identifying similarities across the numerous dimensions of a multivariate process and compressing them into a single representation. As a result of clustering, a complex and difficult-to-understand process gets recast into one that non-technical people can understand. (Sergio et.al.,2020)

In another research by Marco and Fernando, the spatial clustering problem is approached using a Genetic Algorithm (GA). Genetic Algorithms optimisation capabilities are well-known and widely applied in a range of scientific domains. The flexibility provided by GA appears to inspire academics to find new and improved approaches to clustering challenges in geography. A comparative study between k-means, self-organizing map (SOM) and genetic algorithm (GA) showed that GA obtained the lowest value of square error of cluster dispersion. Thereby, GA indicated a good performance for optimization. (Marco & Fernando, 2000)

#### **V. LEAST COST PATH METHOD**

Least-cost path (LCP) algorithms are employed to identify the most efficient route connecting two locations within a cost surface. This surface is typically represented by a raster map, where each cell holds a cost value signifying the traversal difficulty associated with that specific location. The LCP algorithm seeks to minimize the cumulative cost of the entire path, considering the individual cost values of each traversed cell. A line that connects a starting point with a destination can be found using LCPA by creating an accumulated cost surface (Douglas, 1994). The cumulative cost of each cell from the starting point is calculated to create the accumulated cost surface from the cost surface. Considering all factors influencing the pipe routing and combining them through a multicriteria evaluation, the cost surface can be determined. (Atkinson et al., 2005; Bagli et al., 2011) The least-cost path between any destination points and the pre-defined starting point is found by moving backwards from the destination point over the accumulated cost surface, step by step, choosing cells at decreasing value (Singh & Sing, 2017; Yakan & Celik, 2014; Bagli et al., 2011; Lee & Stucky, 1998).

One of the oldest spatial issues is determining the optimal route through a region. Using GIS and Remote Sensing technology, this challenge was recently handled successfully. Several attempts to automate the route-planning process using GIS technology have been done in the recent decade. According to an examination of several studies, the methodology is still in the exploratory stage. In undeveloped countries, traditional route planning was entirely centred on topographical issues such as gradient and curvature. On large-scale topographical maps, the usual procedure is to hand label portions of allowed gradients for route alignment. When a number of elements such as landslides, geology, soil type, vegetation, land-use, and landcover are taken into account, such an approach is complicated and time-consuming. (Rylsky et al. 2005)

A model was developed with a trial implementation for a natural gas pipeline route selection operation for a specific area in Turkey. A least cost pathway method for linear engineering constructions is created using GIS analysis and raster network analysis tools. ArcGIS 9.0 Spatial Analysis Module is used to create the path. The steps for creating such a path are listed below.

1. Generate a Thematic Cost Map (Classify and Weighting)
2. Perform Cost Weighted Distance Calculations
3. Create Direction Datasets
4. Use Distance and Direction Datasets to find the shortest path.

The results show that the route created by this method is more eco-friendly and less expensive than the traditional route. This revealed that automating the route process by Least cost path could have as much as 5-15 percent savings. (Volkan et al., 2006)

An autonomous pipeline route finder method may choose the most convenient path while avoiding geographic and topological obstacles and picking appropriate locations based on their weights. An automatic natural gas pipeline design study was conducted in the east western region of Turkey for this research. The findings were compared to those of The Turkish Petroleum Pipeline Corporation's completed Mus natural gas project. Cost 19.8%, total length 4.4%, forbidden zone uses 90.4%, fault line pass 40%, and number of vertices count 31.17% were all reduced by using GIS capabilities and the lowest cost path distance algorithm. The simplification resulted in a 20% cost savings. Figure 3 shows the comparison of existing route and optimum route for the study area. (AliIhsan et al, 2019)

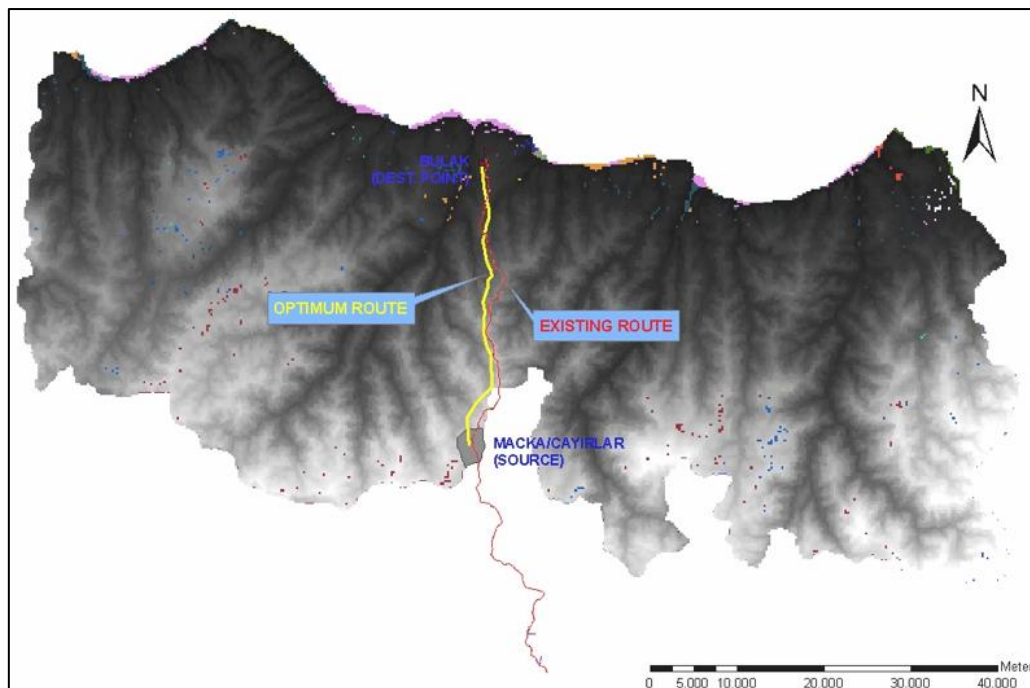


Figure 3: Existing route and Optimum route for a Turkish natural gas pipeline project

## VI. SUMMARY

Traditional irrigation systems, plagued by high water losses, are becoming unsustainable as water scarcity intensifies. Piped irrigation networks offer a solution, but optimal pipeline routes are essential for maximizing efficiency and minimizing costs.

GIS enables the integration of diverse spatial data, including detailed topographic data, land use land cover data, cadastral data, etc. to produce results that are suitable to the real world (Rajesh Kumar et al, 2024). This review explores advanced methods for achieving this are given the table 1.

Table 1: Methods and its benefits for optimum routing

Method	Description
Least cost path analysis with GIS	This method factors in diverse aspects like topography, soil properties, and spatial constraints, leading to the identification of the most economical route for pipeline installation.
Image classification using satellite imagery	This technique provides valuable insights for informed decision-making during pipeline route planning by categorizing land cover features such as vegetation and buildings.
Machine learning techniques like spatial clustering	This approach allows for the grouping of similar areas based on various factors, further aiding in the optimization of pipeline routes.

By adopting these innovative approaches in GIS, irrigation projects can not only improve water use efficiency but also contribute to environmental sustainability and economic viability in the face of growing water scarcity.

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