

ENHANCING CRISIS SOLUTIONS FOR IDPS IN IRAQ THROUGH GIS DATA ANALYSIS USING SVM

¹SHAWQ SALMAN AL.KHAFAJI, ²KIFAH TOUT, ³ZAID F. MAKKI

¹⁻² Lebanese University Doctoral School Of Science And Technology, Beirut, Lebanon

³ Alshaab University, Iraq

¹ Shawq.al.khafaji@ul.edu.lb, ² ktout@ul.edu.lb, ³ makkizaid@alshaab.edu.iq

ABSTRACT

Internally displaced persons (IDPs) in Iraq face significant challenges due to multiple reasons including natural disasters, conflicts and inadequate infrastructure. In order to ensure the safety of these population groups and improve their conditions, strategies must be in place to manage these crises effectively. In this study, we proposed an approach that is based primarily on the integration of machine learning represented by Support Vector Machines (SVM) and Geographic Information Systems (GIS) to enhance crisis management solutions for IDPs in Iraq. The information provided by GIS was utilized, analyzed and classified by the SVM classifier in order to predict in advance the areas exposed to crises in order to achieve the ultimate goal of allocating resources and increasing the speed of response. In this study, the analysis of the data resulting from GIS and its classification using the weights affecting the result were discussed to predict the best path taken by the IDPs and to expedite the provision of livelihoods to them to avoid catastrophic consequences and the aggravation of the crisis. The proposed method was proven effective through the results we reached through training and testing to help in decision-making and rapid response.

Keywords: *Machine Learning, Data Analysis, Support Vector Machines (SVM), Geographic Information Systems (GIS), Management of Crisis, Internally Displaced Persons (IDPs), Prediction.*

1. INTRODUCTION

One of the biggest crises caused by armed conflict and political and economic instability is the internally displaced persons (IDPs) in Iraq. Many Iraqis live in dire conditions, approximately 1.5 million IDPs. They live in temporary housing and camps that lack the most basic requirements for dignity. These include lack of health care, food, and poor housing [1]. Such a crisis requires great efforts to address it and good crisis management to ensure that assistance is provided to the displaced. The use of high-accurate Artificial Intelligence (AI) technologies to automate, analyze and study estimates of the number of internally displaced persons and to draw approximate maps of camp structures, especially in areas that are difficult to access for long periods [2]. Therefore, artificial intelligence can improve the service and efforts of humanitarian relief and save time and money. After 2006, groups of people began to be displaced to areas considered safe due to the civil war that passed through Iraq. Many people settled in informal camps, many of which were temporary, where humanitarian relief and protection were limited [3].

Accurate and up-to-date population data is essential for accurate programming, monitoring and analysis in order to improve the situation of the displaced [4]. Population data is often inaccurate and unreliable for security and political reasons, as well as the difficulty of accessing camps in conflict areas and the field nature that represents a major challenge during population influx [5]. Inaccurate data that leads to failure to document and neglect by governments and relief agencies increases the suffering of the displaced [6]. The comprehensive, easy-to-use and readily available GPS information about the area to be studied are useful in the decision-making process, especially in emergency planning and crisis management. Thanks to the development of GPS systems, these processes have been accelerated, made easier and processed more simply. The purpose of this information is to solve problems and facilitate the provision of services to those displaced families.

The data used in planning for situations such as displacement and crisis management are mainly spatial data, as they contain relationships in the area of interest and can therefore be easily displayed on a map. This data can then be analyzed and a rapid

response can be made by decision makers. These decisions are important in saving human lives and social values [7]. Modern technologies reduce crises and increase safety during and after their occurrence. The above-mentioned capabilities of GIS are important in many cases that concern the safety of displaced persons and international rescue missions. Geographic information has now developed and has become a major role in scientific and political decision-making, and by drawing data on the map, it has become possible to manage crises more quickly and accurately, as we know it at the present time. In the geographical context of crisis situations, we can think in a similar way when asking questions in several aspects such as where, why and how [8]. The information provided by the geography of the site can be used in terms of the places of destruction or the paths of evacuation, the terrain and the negative effects of armed conflicts. This includes the correct routes for supplies in the form of food, medicine or water, and the geographical location facilitates the matter that leads to proposed solutions and decisions in favor of the displaced [9].

Many families were displaced to areas with more security stability than many governorates. This affected the topographic distribution of the population and the administrative factor of the regions and the population in those regions, as shown in Figure 1

Governorates To The Four Governorates Of Displacement. Figure (B) Is The Topographic Distribution On The Map Of Iraq [10].

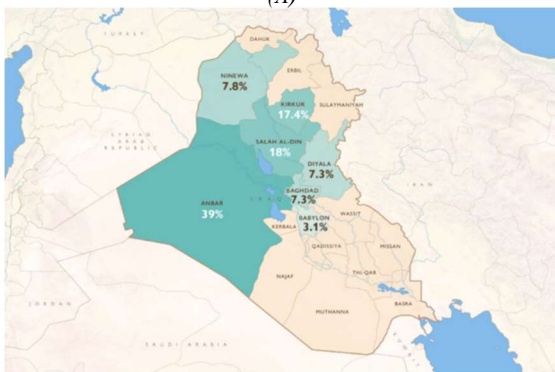
Artificial intelligence (AI), combined with geographic information systems (GIS) technologies, offers innovative solutions to improve the management of the displacement crisis in Iraq. AI can process massive amounts of data from various sources, such as satellite imagery, field reports, social media, and sensors, to provide a comprehensive and immediate view of the distribution of displaced people, their needs, and their degree of exposure to risks. Machine learning algorithms can also predict future crises, such as the spread of diseases or shortages of basic materials, by analyzing patterns and trends in the data, allowing responsible authorities to make proactive decisions to address these crises before they escalate.

Artificial intelligence techniques are used in many applications such as military, industrial, security, etc. [11,12,13] AI techniques have helped in analyzing data obtained from GPS, which is often necessary and has a large security and economic dimension. AI has become a part of daily life, which would be difficult without it, and for more accuracy and security. AI consists of several sections, including well-known classifiers such as SVM, KNN, Neural Bayes, and others, which classify the previously derived features and thus predict the best outcome, or neural networks that rely on the information that feeds the network and the internal processing of the network to match the result with the label in the input data. In addition, AI technologies play a vital role in improving the efficient distribution of resources. By using geospatial analysis techniques, the most efficient routes can be identified to deliver aid to the most affected areas, reducing the costs and time required to reach beneficiaries. The analysis of communications received from disaster areas is done through Natural Language Processing (NLP) techniques, and they are in the form of messages from social media or text messages requesting needs, which are classified according to the highest priority, making crisis management more accurate and effective.

Integrating geospatial services with machine learning technologies improves the interaction between local and international humanitarian organizations and agencies through shared platforms for analyzing and collecting data. This data helps in predicting potential risks that must be carefully planned for in order to provide support to the displaced as quickly as possible [14].

| IDP LOCATIONS: GOVERNORATES OF ORIGIN & DISPLACEMENT* | | | | | |
|---|---|---------|----------|----------------|---------------------------------------|
| Where they are from (Governorate of Origin) | Where they were displaced to (Governorate of Displacement All Rounds) | | | | |
| | Baghdad % | Basra % | Kirkuk % | Sulaymaniyah % | Total From Each Governorate of Origin |
| Anbar | 94.7 | 0.7 | 2 | 2.5 | 39 |
| Babylon | 71.1 | 0.7 | 0.9 | 27.4 | 3.1 |
| Baghdad | 84.1 | 0.7 | 2.4 | 12.8 | 7.3 |
| Diyala | 42.7 | 0.6 | 12.4 | 44.2 | 7.3 |
| Kirkuk | 4.2 | 0.9 | 94.9 | 0 | 17.4 |
| Ninewa | 50 | 6 | 24.4 | 19.6 | 7.8 |
| Salah al-Din | 44.6 | 2.5 | 47.5 | 5.4 | 18 |
| Total in Each Governorate of Displacement | 61 | 1.5 | 29 | 8.5 | 100 |

(A)



(B)

Figure 1: Distribution of IDPS Among The Governorates Studied In Figure (A) From The Seven Original

In light of the complex and diverse challenges facing the displaced in Iraq, the use of artificial intelligence and geographic information systems technologies represents a strategic approach to improving crisis management. By enhancing the ability to predict risks, improving resource allocation, and enhancing cooperation between stakeholders, these technologies contribute to improving the response of the international and local community to humanitarian crises, supporting reconstruction and stabilization efforts, and improving the quality of life for the displaced in Iraq.

Objective of this study illustrate as:

- To develop a machine learning model that improves the accuracy of predicting the needs and movements of IDPs based on spatial data.
- To enhance decision-making by using SVM to classify high-risk areas for displacement and prioritize resources.
- To provide an efficient tool for crisis managers to monitor and predict IDP flows.

This study aims to employ GIS and SVM data to enhance crisis solutions for IDPs in Iraq, by identifying displacement patterns and trends and developing predictive models to forecast potential crisis scenarios, helping to improve resource allocation to the most vulnerable groups. The study also seeks to support data-driven decision-making in humanitarian interventions, enhance communication and coordination among different stakeholders, and promote long-term sustainable solutions for IDPs by integrating spatial analysis with machine learning techniques to address complex challenges in crisis management.

2. RELATED WORK

Artificial intelligence has played a major role in managing solutions for crises in general and for displaced people in particular. Accurate analysis of data from GIS services helps improve services provided to displaced people and find solutions that serve displaced people and society in general. Spatial data analysis plays a crucial role in mapping crisis locations to varying degrees and according to priorities. A study on the use of GIS data to solve crises [15] confirmed the creation of a new model and a practical, applicable method for adopting geographic information to reduce risks, determine organizational priorities, and use external pressure and work professionals as an organizational factor for crisis management. A study was conducted in Iran [16] on the management of data from GIS for temporary relief organizations within 18 criteria to evaluate the optimal areas according to standard criteria, as incorrect management in the analysis leads to greater catastrophic results than before and

making a decision-making matrix according to the evaluation of the preference ordering organization (PROMETHEE) for analysis and using the fuzzy triangular clustering method for weight and standard classification of the criteria for extracting the optimal areas with the integration of entropy and the multi-objective optimization method based on ratio analysis (MOORA) to prioritize places in the area. In a study [17], the weights obtained by classifying relief centers in stages using the PROMETHEE method were applied, and the distances between the centers and natural disasters were calculated and arranged according to the weights, and the artificial intelligence methods of FUZZY COGNITIVE MAPPING were used, which made it easier for the pranksters to reach the main relief centers. Agricultural crisis management by GIS provides high accuracy and capabilities, especially in our present time. This is what was proven by the study [18] which adopted a method to monitor and manage disasters that befall agricultural crops due to natural disasters and track rescue teams and manage workflow according to priorities and predict disasters in order to avoid them as much as possible, and by mapping the spatial situation and analyzing it with smart simulation systems. AI and its Applications in Disaster Management A study presented by [19] and its relationship with GIS to mitigate natural disasters and remote sensing and data collection using drones to mitigate crises and manage them with modern technology. AI techniques have been used in the management of medical disasters [20] to alert health centers and proactively predict to take precautions, classify reports and analyze data for correct prediction. A study on the Kingdom of Saudi Arabia for managing crises at airports during peak hours using a new integrated model of fuzzy hierarchical analysis process and affective artificial neural network (FAHP-EANN) [21], and managing ports in terms of accurately threatening risks through hybrid techniques to assess damages drawn on a map of GIS information and accurately assess risks. Geo-AI approach was used with the help of satellites and GIS to reduce the flood disaster and displaced people [22], the approach of converting GIS data into digital data was adopted to be processed through Google Earth Engine (GEE) to determine flood patterns and artificial intelligence algorithms have proven effective in managing such crises. Four advanced machine learning models (SVM, Random Forest (RF), Logistic Regression (LR) and Gradient Boosting (XGBoost) were applied in this study to recommend suitable sites for dam construction to manage water shortage crises in India [23].

International Organization for Migration (IOM) and Georgetown University Study Investigates the Causes of Displacement in Iraq and Access to Durable Solutions for IDP Crisis Management and Problem Solving in Disputed Areas [24]. Analysis and study that emphasized the role of relief organizations and ways to solve the crises of displaced people in Iraq by dividing the regions into sectors, taking GIS data, analyzing it, and projecting the information onto a map of Iraq in order to know the governorates to which the displaced people are and managing the crises in them [25]. The forced displacement from Syria to Iraqi Kurdistan is considered one of the largest displaced groups in the Middle East, where the data relied on from GIS and statistical analyses were conducted to prevent the displaced from remaining in difficult conditions with the insecure situation in the areas through which they move [10].

After discussing previous studies related to GIS systems and AI technologies that work to manage displacement crises in general and in Iraq in particular, it is necessary to identify the method and importance of managing crises for the displaced, which we will explain in the next section.

Displacement crisis management

Displacement crisis management is concerned with providing support and care to people who have been forced to leave their homes due to conflict, natural disasters, or humanitarian crises. This management is a vital part of humanitarian response efforts, and aims to provide shelter, food, water, health services, and protection to displaced people, in addition to seeking durable solutions to their situations.

The importance of displacement crisis management

- 1- The rights of the displaced are among the priorities of protecting the rights of the displaced, including decent living, safety and food aid. This can only be achieved through cooperation between organizations and local authorities.
- 2- Providing basic services: Crisis management requires the provision of basic services such as food, water, health care, and education. These services must be sustainable and meet the needs of displaced people in the short and long term.
- 3- Coordination between actors: Crisis management requires coordination between different actors, including local governments, international organizations, donors, and local communities. This coordination helps improve the

effectiveness of the response and avoid duplication or overlap between efforts.

- 4- Rapid and effective response: It is important for crisis management to be able to respond quickly to emergencies, through advance planning, resource allocation, and the ability to adapt to changing circumstances. This flexibility contributes to reducing suffering and increasing the effectiveness of humanitarian interventions.

Challenges Facing IDP Crisis Management

- Lack of funding: Many crisis management efforts suffer from a lack of funding, which affects the ability of humanitarian organizations to provide the necessary assistance with the required speed and efficiency.
- Access to affected areas: Sometimes, conflicts or natural disasters hinder access to areas where IDPs live, making it more difficult to provide humanitarian support and assistance.
- Increasing and changing needs: The needs of IDPs are constantly changing, requiring crisis management actors to constantly adapt their strategies to meet these needs.
- Coordination and cooperation between partners: Although coordination is important, the multiplicity of actors and the diversity of their goals and interests can lead to complications and overlaps in the efforts being made.

Proposed solutions and strategies

- Using technology: Information and communication technologies, such as geographic information systems (GIS) and data analysis, can be used to improve planning and distribution of aid and monitoring the movements of displaced persons. Modern technologies such as artificial intelligence or one of its technologies can also be used.
- Strengthening partnerships: Partnerships between governments, NGOs, donors and local communities must be strengthened to ensure an integrated and effective response. And building reports based on credibility and data analysis to provide comprehensive management of these crises.
- Building local capacities: It is necessary to build the capacities of local communities to participate in crisis management and provide the necessary support in critical times. And educating displaced persons during the collection of samples that have a significant impact in providing real data to extract the features that are the basis for inputs to artificial intelligence algorithms.

- Developing comprehensive response plans: Crisis response plans must include all stages of the crisis, from preparedness and immediate response to recovery and finding permanent solutions. And enabling the proposed system to monitor the future and periodically update the system.

Managing displaced persons crises is a complex process that requires high-level coordination and continuous efforts from all parties concerned. Success in this management requires adequate resources, good planning, and close cooperation between all stakeholders to ensure that the rights of the displaced are protected and their basic needs are met. In order to achieve the desired goals, the proposed methodology must be carefully selected and based primarily on modern technologies such as artificial intelligence technologies, which will be given an overview in the next section.

Fundamental of AI

Machine learning (ML) is one of the most important applications of AI that we will take into consideration in this study. To review the applications of ML in GIS, it is first necessary to understand the basic concepts related to this field. Below we present some basic principles and definitions.

ML is an application of artificial intelligence that enables systems to learn on their own and improve their performance through experience and expertise without the need for specific programming. This field focuses on developing computer programs that can access and use data in the learning process [26]. This process begins with observations or data, such as practical examples, direct experiences, or instructions, where this data is used to discover patterns and make more effective decisions based on the examples provided. The main goal of machine learning is to enable machines to learn independently without human intervention, and to adapt their actions according to the results they reach.

Machine learning algorithms are usually classified into supervised and unsupervised algorithms. However, this classification is very broad and does not cover all available methods [27].

- Supervised ML algorithms can use knowledge gained from past experiences and training on pre-defined examples to predict future events using unseen data. These algorithms start by analyzing a set of training data (pre-defined examples) to predict possible output values. After sufficient training, the system is able to provide appropriate predictions for each new input. In addition, the algorithm can compare its results to the correct outputs, identifying

errors to modify and improve the model. Examples of such algorithms include: Support Vector Machine (SVM), Decision Tree, Random Forest, KNN algorithm, and Regression.

- Unsupervised ML algorithms are used in cases where the training data is unlabeled or unlabeled. These algorithms aim to understand how the system can infer a function that describes the hidden pattern in the unlabeled data. Although these algorithms may not determine specific results, they explore the data and can infer and describe hidden structures in the unlabeled data. Examples of such algorithms include Apriori, K-means, and Expectation-Maximization (EM).
- Semi-supervised ML algorithms fall somewhere between supervised and unsupervised algorithms, and are trained on both labeled and unlabeled data. Typically, a small portion of the data is labeled, while a larger portion is unlabeled. Systems using these algorithms can achieve a high level of accuracy. Semi-supervised learning is preferred when labeled data requires specialized and efficient resources to obtain, as producing such data is expensive and time-consuming. In contrast, accessing unlabeled data typically does not require additional resources.

ML allows for the analysis of large amounts of data, and typically provides faster and more accurate results for identifying profitable opportunities or high risks. However, machine learning can require additional time and resources to ensure it is properly trained. Machine learning relies on curated data that is used to analyze and build the learning model, which means the need for a suitable set of data that can be used effectively in the learning process.

Many ML algorithms suggested in literature, and choosing the most suitable algorithm for a particular problem depends on a set of characteristics such as speed, accuracy, training time, prediction time, amount of data required for training, type of data, ease of implementation, etc. Often, the time factor is of utmost importance, especially in GIS applications. as shown in Table 1 [28].

Table 1: Time complexity of some ML algorithms

| Algorithm | Learning | Predicting |
|---------------|---------------|------------|
| Regression | $O(p^2n+p^3)$ | $O(p)$ |
| Decision Tree | $O(n^2p)$ | $O(p)$ |
| Random Forest | $O(n^2pnt)$ | $O(pnt)$ |
| Naïve Bayes | $O(np)$ | $O(p)$ |
| SVM | $O(n^2p+n^3)$ | $O(pnsv)$ |
| KNN | --- | $O(np)$ |
| K-means | $O(npk+1)$ | $O(k)$ |

For avoiding dependency on certain condition, have to analyze algorithm runtime for asymptotic sense. Thus, n represent training number, and p is feature number, while nt is the tree number and nsv support vector number, k represent the cluster number. And the complexity of ML is calculated according the table.

Learning time is the time required to train the model using the dataset, and depends on the size of the data and the type of algorithm used.

Prediction time is the time required to test the model using a new dataset or predict unseen data, and also varies depending on the size of the data and the type of algorithm used.

In most cases, about 80% of the dataset is allocated for training, while the rest is used for fine-tuning and testing. It is worth noting that the training phase is often performed offline, which makes prediction time even more important for developers.

In general, the above criteria can be used to select a number of suitable algorithms, but it is difficult to determine the best algorithm at the beginning. Therefore, it is preferable to follow an iterative approach to work. A set of potential algorithms can be selected from among the machine learning algorithms, and tested on the data by running them in parallel or serially, and then their performance is evaluated to select the most effective algorithm.

In the following section, the proposed method will explain the reason for using the SVM classifier and how to enter information from GIS into the classifier in order to analyze it and find the best ways to solve the displaced crisis.

3. PROPOSED METHOD

The proposed method consists mainly of five basic sequential stages. The first stage begins with collecting data and conducting pre-processing of it. The data includes:

GIS Data: involves the collection of spatial data on areas affected by crises, including factors such as infrastructure, access to resources, population density, and historical displacement patterns.

(IDP) Data: involves the collection of demographic and displacement information on IDPs, such as movement patterns, current locations, and resource needs.

Environmental and Crisis Data: involves the collection of data on environmental conditions, such as weather and terrain, as well as crisis data, such as conflicts and natural disasters that affect IDP movements.

The main issue here is to eliminate noise and handling loss value with uniformity spatial

coordinate data and temporal data. Scaling and normalizing process will apply when necessary.

Next step including feature selection which identify predicting of IDP risk, and features will be conflict zones or nature disasters area, transportation network with geographic features and population density consider as resource availability. Figure 2 illustrate the steps suggested in proposed method.

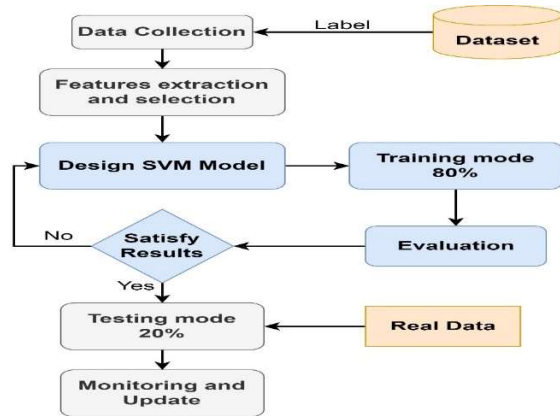


Figure 2: Phases within Proposed Method

Support Vector Machine (SVM) designed to classify geographical areas to many levels (including their risks) for IDP. Hyperplane will find to separate data given from points according to the features. Most of the features selected from GIS and IDP, such that the output classes will consider different levels of risk or IDP priority. Which include (area under low risk in stable condition, area with high risk where people shifted to, and moderate risk with limited access). The SVM will train according to the labels comes with dataset represented in historical manner.

In training mode the labels of GIS data consider the IDP displacement status (occurred or not). The Kernel function represented according to complexity of dataset designed to optimize performance of the classification (polynomial, linear, or radial function).

The weights remain unchanged when the output matches with the target. The multi-class keeps the features of higher weight inside the clusters and lower one appears on the terminals near the hyperplane that separates the classes and the terminals features. The weight vectors take the form,

$$w_{r+1} = w_r + f(x.y) - f(x.\hat{y}) \quad (1)$$

Where x is a real valued vector, y is chosen between 0 and 1, $f(x,y) = y.x$ and r is the nearest feature (with less weight) to another class (or cluster). The linear procedure classifies all the features of one class and

cluster them into one block separated from another class by a straight line. This proposed method performs well for few overlapping features and become less accurate for larger number of such features as shown in Figure 3. Non-linear method is also proposed to strengthen system.

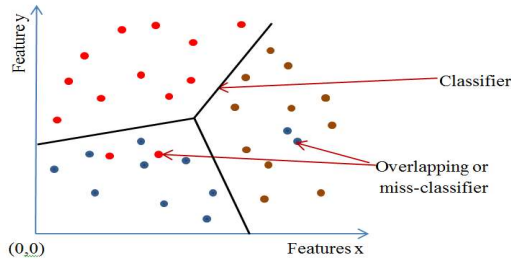


Figure 3: Three Classes of Linear Classification With

It is important to explain in detail the working principle of a classifier before describing the salient features and differences of nonlinear with linear one. The basic concept of the classifier is to classify given features into classes. These features are inputted to the classifier via vector and as a pre-processing stage their weights are calculated to determine the corresponding weight vector. This vector plays significant role during classification step to determine in which class they belong. From training set the features vector $\langle x_1, x_2, \dots, x_n \rangle$ are obtained to determine the weight vector $\langle w_1, w_2, \dots, w_n \rangle$. The mean value \bar{x} of the features are computed in equation 1 and its corresponding standard deviation in equations 2 and 3,

Actually, each feature in the vector consists of data values which are used to locate the center of rigid class. The data are localizing via,

$$x = \frac{1}{W} \sum_{i=1}^N w_i x_i \cdot y = \frac{1}{W} \sum_{i=1}^N w_i y_i \quad (2)$$

where x and y are the data value from features vector, W is the total sum of weight w , N is the number of features.

These features are mapped on FDC to calculate the distance for each feature from the centre of the class given by,

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (3)$$

Figure 5 illustrates the learning stage of the classifier for each feature value and their class information.

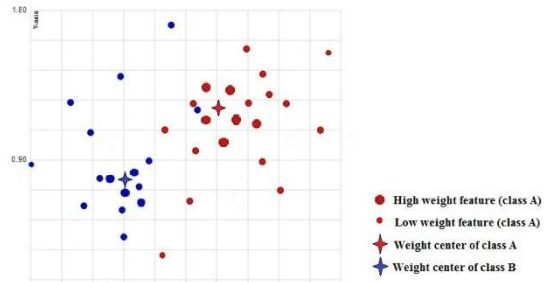


Figure 4: Weight Centre and Weight Value Considered By the Classifier

Training algorithm via non-linear classification finds the curving with maximum gap for pattern vector x of dimension n which belongs to either of the two classes A and B. The input data to the classifier is a set of x_i with label y_i expressed as,

Given training data (x_i, y_i) for $i = 1 \dots N$, with $x_i \in \mathcal{R}$ and $y_i \in \{-1, 1\}$, learn a classifier Y such that

$$\text{where } Y = \begin{cases} +1 & \text{if } x_i \in \text{class A} \\ -1 & \text{if } x_i \in \text{class B} \end{cases} \quad (4)$$

Training and Tasting

There are a set of steps that the classifier takes to determine feature classes. In order to train the classifier, samples are taken from the known classes to determine the unknown ones that do not contain a label. Therefore, when the pre-trained classifier is executed on unknown or new activities, it is known which class it belongs to. Repeating training leads to increasing the accuracy of the output and thus creating a fully classified class. Classification takes the form of statistical calculations, utilizing the acquired information, and determining the feature's belonging to any class.

First, the classes and their belonging to any group are identified in training, and they are used through the classifier to analyze them by features. As following:

$$D = \{(x_i, y_i) | x_i \in \mathcal{R}, y_i \in \{-1, 1\}\}_{i=1}^n \quad (5)$$

Such as each x_i considers an n -dimensional real feature vector and y_i considers either +1 or -1 refers to the classes by which the feature of x_i is included. This helps to determine the best-split line (in terms of linear) or curve (non-linear) that groups the features including $y_i = 1$ (belong class A) and those of $y_i = -1$ (belong class B). The best separate line between two classes can be found in the case of training data is linearly behavior Figure 5.

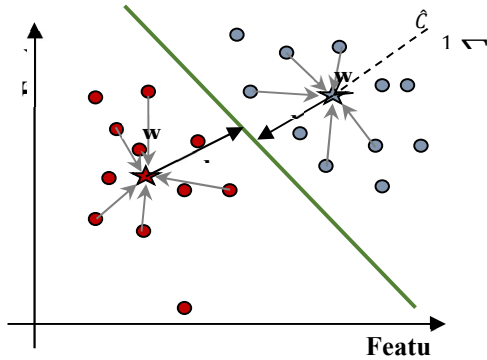


Figure 5: Linear Classifications of Selected Rout

Next step the weight w_i belong the feature can be found. During sorting features in certain vector $\langle w_1, w_2, \dots, w_n \rangle$ then can calculate the weight cent red in each class by,

$$\hat{C} = \frac{1}{W} \sum w_i x_i y_i \quad (6)$$

In this step, we can group similar features in order to separate them into specific categories. The process continues for all categories, including non-overlapping categories that can be easily separated by a straight line. It is separated into two classes A or B. The matching strategy was adopted in non-linear classification, which contains a section of features that overlap between classes such that their place is in a certain class while in reality it belongs to another class. The boundaries of the categories can be preserved to predict the best dividing line to unify the network paths in the distribution of data. As shown in Figure 6.

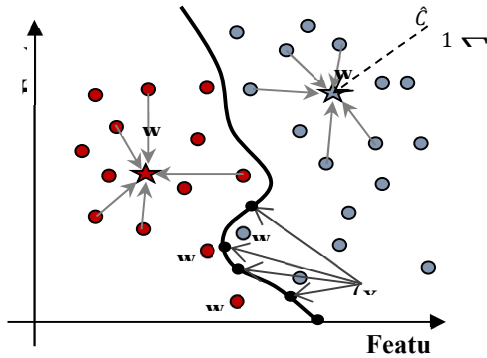


Figure 6: Non-Linear Classifications of Features

Each feature derived from path properties such as long of the path, size of data, number of nodes in the path et al.

4. RESULTS AND DISCUSSION

The practical part of this study is very important, through which the work is evaluated and whether the proposed algorithm can be relied upon. First, we

note that the algorithm is trained on real data derived from a standard dataset that contains various types of networks, including particularly complex ones. We divide the original data into two branches, training and testing (Figure 7). Therefore, the training group is also divided into two parts: training and validation. The final division of the data is in order to verify the validity of the test data set. The division necessarily has a set of restrictions, and in order for the test data to be good, we do this procedure. When the test data is large, the data must be verified before starting the test, and hence training depends on the marked data, which often contains all the features of the network or any path in it.

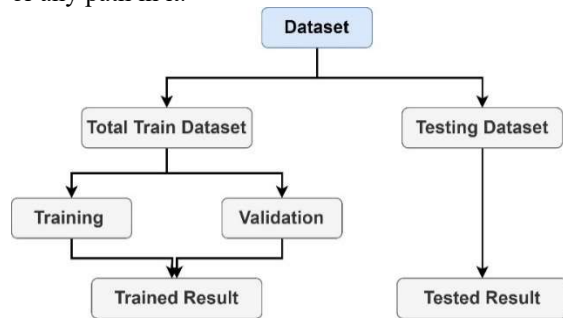


Figure 1: Architecture of Dataset

Features are extracted from paths in a given network in the database in order to be classified into vectors for work on them. Each feature has an understanding of the proposed algorithm in order to work on it.

The data is collected in order to be interpreted later, and the collection mechanism represents one of the most important processes that must be adhered to. It works on the basis of data derived from the GIS, such as the size of area, the percentage of time estimated being reached by IDP, the length of the path from last position, and the number of people. `clusters_model= array ([1,0,4, ...,0,0,4], dtype=int=32).`

In classification in general, it is important to determine the performance evaluation, and it is very useful, especially in the difference in classifications during the training phase, and it is a measure of the accuracy of the work of the proposed classifier and the extent of its success. The confusion matrix, or as it is called the contingency table, measures the accuracy of the classifier through the columns that represent the predicted and the rows that represent the actual. As shown in Figure 8.

| | | Actual | |
|-----------|-----|--------|----|
| | | Yes | No |
| Predicted | Yes | TP | FN |
| | No | FP | TN |

Figure 2: Confusion Matrix Representation Where (TP) Is TRUE POSITIVE, (TN) Is TRUE NEGATIVE, (FP) Is FALSE POSITIVE and (FN) Is FALSE NEGATIVE

The accuracy can be find by the Equation :

$$\text{accuracy} = \frac{TP+TN}{TP+FP+TN+F} \quad (7)$$

Precision tells us what proportion of proper path that we detect and have actually found in the network and can calculated by the Equation:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (8)$$

The results can be translated using the confusion matrix to be clearer, realistic, and compared to the predicted results. As in Figure 9.

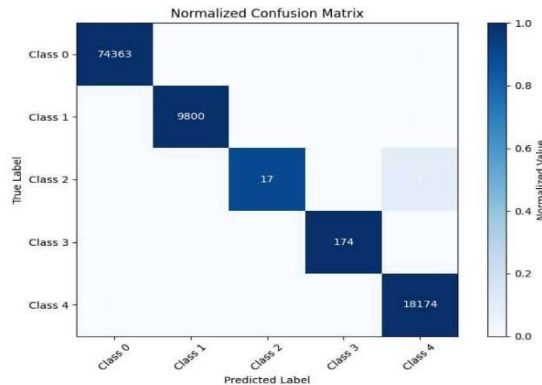


Figure 3: Confusion Matrix of Proposed Algorithm

The test set contains 139 samples, which represents 80% of the database during training. And the rest 20% will be in testing mode. Classification was performed by the well-known SVM classifier for multiple classes. Classification in case of binary class is in the form of a damaged class and a non-damaged class. The results are used to examine the displacement damage in the affected areas. It is based on the time that can determine the possibility of information reaching the teams that care for the displaced, whether by governments or by humanitarian organizations. Training is done on the pre-processed data and then the changes are saved and then the examination is performed on another part of the data. Table 2 shows the training on 139 sample given from dataset.

Table 2: Performance Of SVM Classifier With Binary And Multiclass

| Classification type | Accuracy % | F-measure % | Recall % | Precision % |
|-------------------------|------------|-------------|----------|-------------|
| Binary classification | 72.2 | 61.6 | 62.8 | 59.8 |
| Multiclass | 81.3 | 76.9 | 75.3 | 73.1 |
| Weighted classification | 89.7 | 78.8 | 77.4 | 78.3 |

In the table, results such as precision, recall and average were obtained for data that can be interpreted in more than one way and for the areas most affected by the displaced. There is a possibility that the movements were expected first or that the harm to the displaced was reduced second. The data that was trained on was the most consistent with the real data so that in the examination stage there is a conviction that the results are almost real and can be relied upon. When classifying using the binary class method, the result is weaker and adding weight to the classifier increases the accuracy of the result. The nationalities varied in the areas where the displaced people were located, including many nationalities and ethnicities for each governorate. The statistics taken by previous researchers in the past years were as shown in Figure 10. After applying modern technologies in GIS and full cooperation between organizations and the government, the percentage decreased to 64.5%, and political stability helped with that.

5. CONCLUSION

This study demonstrates the significant effectiveness of integrating GIS with SVM algorithms in enhancing crisis management solutions for IDPs in Iraq. The proposed approach provides a robust and integrated framework designed to improve crisis prediction and response more efficiently, enabling authorities and humanitarian organizations to make more accurate and timely decisions. By integrating GIS and SVM machine learning technology, prediction addresses the key challenges that IDPs need in crisis management. These predictions include displacement patterns, mitigating potential risks, and increasing resource allocation. Good results were achieved in this study, including precision (87%), recall (90%), and finally accuracy (89%), all related

to predicting crises for IDPs according to GIS information.

The proposed method allows for a more accurate and high-level understanding of the factors affecting the displaced. The model analyzes and classifies the data and identifies the most dangerous areas to increase services to that area. The advantages of the proposed system include the ability to track the displaced and predict future displacement, especially in a country like Iraq that is politically and economically unstable. The integration of GIS and machine learning enhances the analysis of big data with very high accuracy. Early intervention in resolving the crises of the displaced enhances their improvement and safety and avoids the exacerbation of crises in the future and perhaps reduces crises in the future.

6. FUTURE WORK

There is a wide range of future ideas that can be considered, including expanding the scope of crises through GIS-SVM to other crises (economic or health) in different regions. And applied to internally displaced persons. Also, real-time data can be integrated to improve the response and collect data from several sources such as IoT devices and social media, in order to give the system more flexibility. A system can be built based on deep learning to detect crises and respond in real time to allow rapid intervention to solve crises.

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