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# Finding the Optimal Prediction of the Occurrence of Earthquakes Using Markov Chains and Artificial Intelligence Methods

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**Abstract**

In this research, a method for predicting earthquakes was presented, where seismic data for the Syrian coastal region were studied for the period from 1996 to 2011, which included the earthquake strength, intensity, location and date of occurrence. In light of the analysis of this data, a method for prediction using Markov chains was determined for a specific period. After that, this process was improved using one of the artificial intelligence methods, which is the machine learning method using the random forest method. Due to this improvement, better accuracy in the results was obtained.The research presents an advanced approach to earthquake predictions by integrating artificial intelligence techniques with Markov chains, thus obtaining the proposed predictions that enable communities to take better preventive measures and remove risks from the population. This will lead to reducing losses in lives, property and infrastructure as much as possible. This is the goal of all studies related to predicting earthquakes in the world and of all types

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## 1. Introduction

Earthquakes are one of the natural phenomena that threaten human life and property, and accurate earthquake prediction can help reduce human and material losses. Markov chains and machine learning using random forests have been used as mathematical tools to improve prediction accuracy. Since earthquake prediction is a major challenge in the field of seismology, the ability to predict the time, strength, and location of earthquakes is crucial to protecting people and infrastructure. With the development of artificial intelligence and machine learning techniques, there are good opportunities to improve the accuracy of predictions. This research is based on the use of Markov chains as a powerful mathematical tool to predict sequential events such as seismic activity. Despite progress in understanding seismic mechanisms, accurate prediction of the time and location of earthquakes remains difficult. In recent years, attention has been directed towards using artificial intelligence techniques, such as machine learning, to analyze seismic data that may have occurred previously. Since Markov chains are statistical models used to model dynamic systems, the future state of the system depends only on its current state. When Markov chains are combined with artificial intelligence algorithms, their ability to predict earthquakes can be improved by analyzing additional data and not limited to specific data such as depth. Depth, tectonic plate effects, and other data can be added to support the prediction process. The Python language program was used to analyze the data and obtain the results.

## 2. Material and methods

### 1. Theoretical aspect:

1.1. Data processing:

After collecting seismic data from the Syrian Seismic Monitoring Authority, which includes data: Earthquake (Magnitude), focus (Depth), date and geographical location

The Syrian coast was divided into eight geographical regions, after which the data was cleaned of abnormal and missing values. Then the time units were unified ( Monteiro, T. 2024 ).

1.2. Markov chain model:

First - Dividing the data into cases based on specific ranges of earthquake strength and depth.

Second - Calculating the transition matrix that represents the probability of transitioning from one case to another ( Al-Khayyat , et. al. 2011).

Third - Finding a prediction of the required seismic events during a specific time period.

Definition of Markov Chains

A Markov chain is a sequence of random variables with discrete values $x_1, x_2, x_3, x_4, \ldots$ Which represents the conditional distribution of the value xn+1 by realizing the values of the random variables $x_1, x_2, x_3, x_4, \ldots$ It depends only on the value xn and in a clear mathematical expression

$$P_{jk} = P_r \{X_{n+1} = k/X_n = j\,, \underbrace{X_{n-1} = j_1\,, X_{n-2} = j_2\,, X_{n-3} = X_{n-3}\,, \ldots, X_0 = j_{n-1}}_{\text{neglect}}\} \qquad (1)$$

This equation can be written according to Markov logic as follows:

$$P_{jk} = P_r \{X_{n+1} = k/X_n = j\} \qquad (2)$$

Some symbols can be defined:

$P_{jk}$ : represents the probability of the random (stochastic) process at the value j in step (n) and will be at the value (k) in step (n+1), which clearly means that there is a discrete parameter space for the random (stochastic) process, i.e.:

[ $X_n$ , n = 0,1,2,3,4,....]

$x_n = j$ : means that the random (stochastic) process is at the state or value (j) at time (n) or step (n)

$x_{n+1} = k$ : means that the random stochastic process is at the state or value (k) at time or step (n+1) In the case of defining Markov chains clearly and precisely, the following is:

((Markov chains mean the value of the phenomenon in the future. They depend only on the current value of the phenomenon and not the previous or historical values)).

Also, the transitional probabilities (one-step transition) from the state or (value) at time (n) to the state or value (k) at time (n+1) can be assumed to be stationary during time. The transitional probabilities, which represent the transition from (Ej) to (Ek), can be represented in a more appropriate form by arranging them in the form of a square matrix as follows ( Ahmad and Sulaiman 2024 ) (Alshimerty and Al-harithy, 2017 )

$$\begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ . \\ . \end{array} \begin{array}{c} \begin{array}{cccccccc} 0 & 1 & 2 & 3 & 4 & 5 & . & . \end{array} \\ \begin{bmatrix} p_{00} & p_{01} & p_{02} & p_{03} & p_{04} & p_{05} & . & . \\ p_{10} & p_{11} & p_{12} & p_{13} & p_{14} & p_{15} & . & . \\ p_{20} & p_{21} & p_{22} & p_{23} & p_{24} & p_{25} & . & . \\ p_{30} & p_{31} & p_{32} & p_{33} & p_{34} & p_{35} & . & . \\ p_{40} & p_{41} & p_{42} & p_{43} & p_{44} & p_{45} & . & . \\ p_{50} & p_{51} & p_{52} & p_{43} & p_{54} & p_{55} & . & . \\ . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . \end{bmatrix} \end{array}$$

The matrix (P) can be defined as follows:

(P) can be called homogeneous transitions or stochastic matrix because all transitional probabilities ($P_{jk}$) are fixed and independent of time and probabilities ($P_{jk}$) must meet the following conditions:

1. $\sum_{k \in E} p_{jk} = 1$ for all values of j and dependent on E.
2. $\boldsymbol{P_{ij} \geq 0}$ for all values of j, k .

We only know the one-step transition probability (Unit- step) or (one-step) which is the probability when the random variable in step ($x_n$) after we know its value and it is in step ($x_{n-1}$) and its value in step ($x_{n-1}$) has been given (known given) and it is the probability of the result of the random process in step (n+h) or the attempt (n+h) so that it was given (given) or that the previous step is known, and this can be symbolized by ($P_{jk}$) .

($P_{jk}$) is the probability of transitioning for one step and from the state or value (j) of the random variable (the random process) to transition to the state or value (k) which is the immediate subsequent step to the state in which the random variable was in the value (j) and its writing is symbolized as follows (Al-Khayyat, 2011 )( Raza , 2023) :

$$P_{jk} = P_r \{ X_{n+1} = k / X_n = j \}$$

But when the transition is for more than one step or more precisely, the transition probability for M steps and from the state or (value) (j) to the state or (Value) k is as follows:

$$P^m_{jk} = P_r \{ x_{n+m} = k / x_n = j \} \quad (3)$$

($P^m_{jk}$) can be defined as the transition probability of the random process from the state or value (j) in step (n+h) to move to the state or value k and the random process (random) in step (n+m) and this means that the random process has cut (m) of the steps, and in a clearer sense that ($P^m_{jk}$) is the transition probability from the state or value j to the state or value k in m of the steps and therefore it is:

$$P^2_{jk} = P_r \{ x_{n+2} = k / x_n = j \}$$

This means that the random process (stocastics) has reached the state or value k after it was in the state or value (j) in two steps and through some secondary steps and we symbolize it with (r) of the steps as follows:

$$P_r \{ x_{n+2} = k , x_{n+1} = r / x_n = j \} = P_r \{ x_{n+2} = k / x_{n+1} = r , x_n = j \} \quad (4)$$

$$* P_r \{ x_{n+1} = r / x_n = j \} = P_{rk} * P_{jr} = P_{jr} * P_{rk} \quad (5)$$

$$P_{jk}^{(2)} = \sum_r P_{jr} \; P_{rk} \quad (6)$$

By mathematical deduction, it is possible to obtain:

$$P_{jk}^{(m+1)} = \sum_r P_{rk} \; P_{jr}^{(m)} \quad (7)$$

$$P_{jk}^{m+n} = \sum_r P_{rk}^{(n)} \; P_{jr}^{(m)} = \sum_r P_{jr}^{(n)} \; P_{rk}^{(m)} \quad (8)$$

After that, the elements of the matrix ($p^2$) are the same elements of the matrix that can be obtained by multiplying the one-step transition probability matrix (p) by itself twice, which means

$$P^2 = p \,.\, p = p^2$$

And similarly

$$P^{(m+1)} = p^m \,.\, p = p \,.\, p^m \quad (9)$$

And also

$$P^{(m+n)} = p^m \,.\, p^n = p^n \,.\, p^m \quad (10)$$

After this theoretical presentation of how to obtain the transition probability matrix, we find that Markov chains can be used to predict earthquakes by analyzing the temporal and spatial patterns of earthquake occurrence.

The Markov chain model is based on the idea that future occurrence depends only on the current state, and not on the entire sequence of previous events, which makes it a suitable tool for studying systems that exhibit time dependence such as earthquakes( Jamal Alden and Sulaiman . 2023 ) .

How to use Markov chains in earthquake prediction:

**1- Determining states:**

The earthquake range is divided into specific states based on factors such as earthquake (Magnitude), depth, or location. For example, states can be defined based on earthquake strength (weak, medium, strong)

**2. Creating a transition matrix:**

Analyzing historical data to determine the transition probabilities between different states.

3. **How to perform the prediction process:**

Using the transition matrix and the current state, the future probability of each state can be predicted. The current state is multiplied by the transition matrix to obtain the probabilities of future states .

## 3. Artificial intelligence

### 3.1 Random Forests

Random Forests are used in machine learning. They are a prediction algorithm created in 1995 by Ho and formally proposed by Adele Cutler and Leo Breiman in 2001. As we will see, they combine the concepts of random subspaces and bagging (Ahmed , Kalakech , A. , And Steiti A. 2024 ) .

A random forest consists of multiple decision trees, trained independently on subsets of the learning dataset (the ensemble method). Each tree produces an estimate, and the resulting set is the one that yields the final prediction with the lowest variance. In short, it's about drawing inspiration from different perspectives, tackling the same problem, to better understand it. Each model is randomly distributed across subsets of decision trees (Rosidi, 2023 ) .

### 3.2. Random Forest Algorithm

A random forest is a machine learning model that relies on:

1. Combining multiple decision trees to improve accuracy, reduce errors, and reduce correlation between feature data. The basic idea is that each tree produces a prediction, and then the predictions of all trees are combined to obtain the final result ( Abdulhady, 2000 ).

2. An equivalent amount of data is randomly selected from the training sample in the original training dataset. Furthermore, a subset of features is randomly selected to generate the decision tree ( Aljuborey, and Shukur 2022 ) (Breiman, 2001 ).

Using these two forms of randomization reduces the correlation between each decision tree, mitigating the potential for overfitting and improving model accuracy. Random Forest is a machine learning technique that combines multiple decision trees to reduce the correlation between feature data (Ahmed , Kalakech , And Steiti A. 2024 )..

Random Forest is used in classification and regression. This algorithm is based on the concept of "ensemble learning," where multiple decision trees are constructed and used together to improve prediction accuracy and reduce the problem of overfitting ( Burkov, 2019 ) .

### 3.3. Prediction Process Using the Random Forest Algorithm

For prediction purposes, this algorithm is used to apply regression. Based on an ensemble system, the Random Forest Regression consists of averaging the predictions obtained from all the decision tree estimates of the Random Forest (Hastie et al, 2009 ) .

The results of the trees are combined to obtain the final prediction. The idea can be summarized as follows ( Bonaccorso. 2018 )

1. Data Partitioning:

The data is divided into a training set and a test set.

2. Tree Construction:

a. A large number of trees are constructed, and each tree is trained independently.

b. For each tree:

- Random sampling: A random sample of the data (pre-sampling) is taken from each tree.
- Random features: At each split point in the tree, a random set of features is chosen instead of using all the features.

3. Aggregating predictions ( Chandra , and Hareendram. 2014 ):
A - In the case of classification, voting is performed among all trees, with the most common result being the final result.
B - In the case of regression, the arithmetic mean of the predictions of all trees is calculated.
C - The predictions of all trees are combined, and a vote is taken (in the case of classification) or an average (in the case of regression).

**4. Reducing overfitting**
By using random samples and feature subsets, random forests reduce the likelihood of overfitting compared to a single decision tree.

**5. Model evaluation**
The accuracy of the model is evaluated using a test set.

6. Advantages of random forests ( El Koshiry , A., et al. 2022).:
A. Ease of use and minimal initialization required.
B. Works well with large and complex data.
C. Reduces the problem of overfitting.

7. Disadvantages of Random Forests:
- Slow training: Due to the construction of a large number of decision trees.
- Difficulty interpreting: Due to the complexity of the model compared to a single decision tree.

## 6.Applied Aspect

In this section, we will forecast earthquakes that may occur on the Syrian coast for a month after the last earthquake recorded in the data under analysis, using the Markov chain prediction method, according to the following steps. After the analysis is complete, the results will be improved using the Random Forest method, which is an artificial intelligence method.

### 6.1 Applying Markov Chains

First - Prepare the data
Second - Divide the data into the required cases to find the transitional probability matrix, so that the earthquake strength was divided into five cases, which are as follows:
Dividing earthquakes into categories based on (MAGNITUDE):
Determining the categories: Earthquakes were divided into categories based on MAGNITUDE values
[0.001, 1.0]: Very Low earthquakes.
[1.0, 1.5]: Low earthquakes.
[1.5, 2.0]: Moderate earthquakes.
[2.0, 2.5]: High earthquakes.
[2.5, 11]: Very High earthquakes.
After applying the Markov chain, the following results appeared
1- The transitional probability matrix was obtained, which is as follows:

Table No.1 Transition matrix of primary Markov chains

| | Very Low (0.001-1.0) | Low (1.0-1.5) | Moderate (1.5-2.0) | High (2.0-2.5) | Very High (2.5-11) |
|---|---|---|---|---|---|
| Very Low (0.001-1.0) | 3.33E-01 | 3.33E-01 | 0.333333 | 3.33E-11 | 3.33E-11 |
| Low (1.0-1.5) | 1.54E-01 | 4.62E-01 | 0.307692 | 7.69E-12 | 7.69E-02 |
| Moderate (1.5-2.0) | 4.55E-13 | 3.18E-01 | 0.545455 | 9.09E-02 | 4.55E-02 |
| High (2.0-2.5) | 1.43E-11 | 1.43E-11 | 0.428571 | 5.71E-01 | 1.43E-11 |
| Very High (2.5-11) | 5.00E-12 | 5.00E-11 | 0.5 | 5.00E-01 | 5.00E-11 |

We see the cases and categories by which the earthquake strength was divided. We notice that the sum of the probabilities of each case equals one, i.e. the sum of each row equals 1.

Note: Since the prediction process in these methods does not take into account the physical properties indicated by the data, but rather performs purely mathematical operations, some results may have negative values, which contradicts physical principles. For example, the depth cannot be negative, so it was necessary to place limitations within the program so that the calculation stops at them. A value of 50 meters was set as the minimum that the earthquake depth could reach.

4. The prediction table for a period of one month after the last earthquake in the data was as follows:

Table No. 2 Predictions of earthquake events for a period of one month

| No | DATE | MAGNITUDE | DEPTH | LOCATION |
|---|---|---|---|---|
| 0 | 2011-03-18 | 1.790282 | 7.059661 | 1 |
| 1 | 2011-03-19 | 1.526062 | 21.575126 | 2 |
| 2 | 2011-03-20 | 1.200211 | 25.743515 | 4 |
| 3 | 2011-03-21 | 1.162485 | 24.437556 | 6 |
| 4 | 2011-03-22 | 1.649363 | 15.343216 | 4 |
| 5 | 2011-03-23 | 2.230732 | 26.195428 | 1 |
| 6 | 2011-03-24 | 1.750609 | 2.648759 | 7 |
| 7 | 2011-03-25 | 1.301182 | 25.923142 | 6 |
| 8 | 2011-03-26 | 0.664042 | 3.346988 | 6 |
| 9 | 2011-03-27 | 1.293462 | 6.818626 | 4 |
| 10 | 2011-03-28 | 6.982569 | 0.050000 | 2 |
| 11 | 2011-03-29 | 1.896538 | 3.021151 | 4 |
| 12 | 2011-03-30 | 1.368123 | 19.455265 | 1 |
| 13 | 2011-03-31 | 1.050867 | 3.317950 | 7 |
| 14 | 2011-04-01 | 1.290759 | 17.648121 | 1 |
| 15 | 2011-04-02 | 1.045660 | 7.428350 | 6 |
| 16 | 2011-04-03 | 0.353517 | 6.885184 | 3 |
| 17 | 2011-04-04 | 0.394699 | 22.670838 | 5 |
| 18 | 2011-04-05 | 1.780040 | 15.351166 | 7 |
| 19 | 2011-04-06 | 1.277020 | 8.237062 | 6 |
| 20 | 2011-04-07 | 1.225433 | 5.967557 | 1 |
| 21 | 2011-04-08 | 1.375798 | 2.171065 | 1 |
| 22 | 2011-04-09 | 1.514652 | 13.681308 | 1 |

| | | | | |
|---|---|---|---|---|
| **23** | **2011-04-10** | **1.303445** | **1.401073** | **7** |
| **24** | **2011-04-11** | **0.611996** | **4.392425** | **6** |
| **25** | **2011-04-12** | **0.430152** | **3.804023** | **6** |
| **26** | **2011-04-13** | **0.642979** | **6.224188** | **7** |
| **27** | **2011-04-14** | **1.216029** | **26.856671** | **5** |
| **28** | **2011-04-15** | **1.023824** | **10.974523** | **6** |
| **29** | **2011-04-16** | **1.855089** | **16.362289** | **4** |

In order to find the quality of the model, two statistical measures of quality were applied, which are:

1- Mean Squared Error (MSE) $= \sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}$ ( 11 )

2- Mean Absolute Error (MAE) $= \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{n}$ ( 12 )

**The results were as follows**

| | |
|---|---|
| **MSE:** | **0.2** |
| **MAE:** | **0.38** |

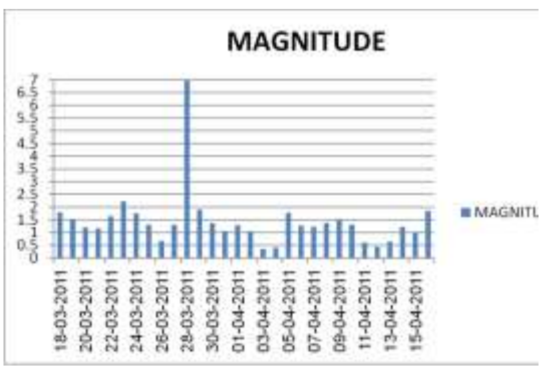


Figure 1: A graph showing earthquake strength and frequency ratings

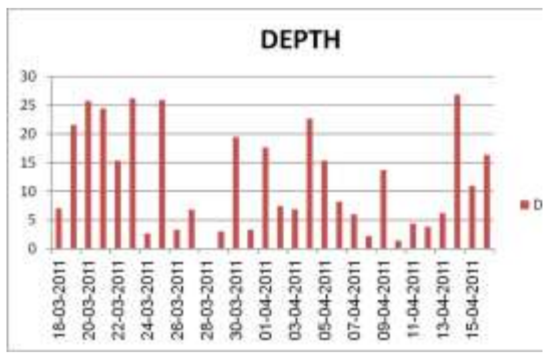


Figure 2: Shows the depth and frequency of earthquakes.

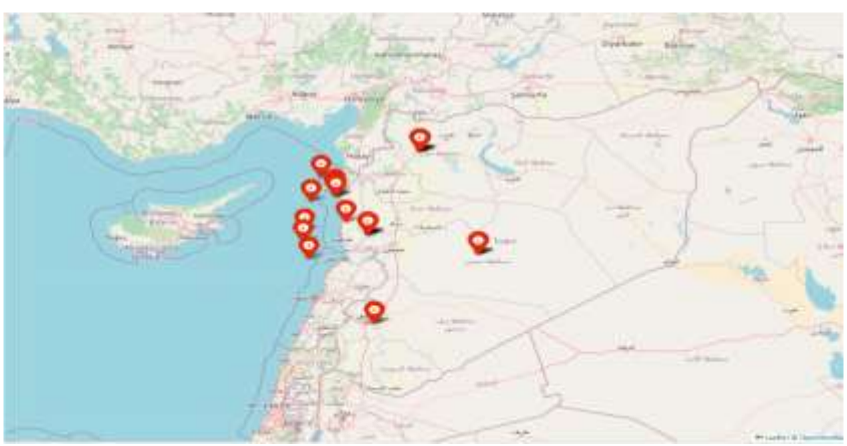

Figure 3 Map of the Syrian coast with expected earthquake incidents distributed on it

### 6.2Application of the Random Forest Algorithm to Markov Chains (Results Improvement Process)

Result Optimization Process
This process was carried out using a machine learning method, the Random Forest method, due to its greater suitability than other machine learning methods based on the research data. In this method, additional variables were incorporated into the strength variable, namely location and depth. This method was better able to accommodate the influence of other variables such as location and depth, increasing its accuracy.
The data was divided into two parts. The first part was the training data, comprising 80% of the data. This was due to the relatively limited data available, which required enhancing the training process.
The second part of the data was for testing purposes, comprising 20%. The trees were then constructed and the remaining steps of the Random Forest algorithm were followed. After the integration and analysis process, the following results were obtained:
1- The prediction table for a period of one month after the last earthquake in the data after the improvement process was as follows:

Table No. 3 Predictions of earthquake events for a period of one month after the improvement process

| No. | DATE | MAGNITUDE | DEPTH | LOCATION |
|---|---|---|---|---|
| 0 | 2011-03-18 | 1.713 | 20.274374 | 2 |
| 1 | 2011-03-19 | 1.247 | 16.216391 | 6 |
| 2 | 2011-03-20 | 1.649 | 6.192963 | 5 |
| 3 | 2011-03-21 | 1.775 | 25.671444 | 5 |
| 4 | 2011-03-22 | 1.322 | 12.433118 | 2 |
| 5 | 2011-03-23 | 1.309 | 11.093568 | 2 |
| 6 | 2011-03-24 | 1.275 | 16.440500 | 7 |
| 7 | 2011-03-25 | 1.348 | 2.224708 | 1 |
| 8 | 2011-03-26 | 1.298 | 8.310520 | 2 |
| 9 | 2011-03-27 | 1.293 | 10.076005 | 2 |
| 10 | 2011-03-28 | 1.759 | 20.903288 | 6 |
| 11 | 2011-03-29 | 1.495 | 4.500008 | 7 |
| 12 | 2011-03-30 | 1.340 | 11.054593 | 4 |
| 13 | 2011-03-31 | 1.573 | 0.150368 | 5 |
| 14 | 2011-04-01 | 1.182 | 16.098304 | 1 |
| 15 | 2011-04-02 | 1.366 | 0.050000 | 1 |
| 16 | 2011-04-03 | 1.447 | 17.836469 | 7 |
| 17 | 2011-04-04 | 1.546 | 7.955699 | 4 |
| 18 | 2011-04-05 | 1.609 | 19.995218 | 1 |
| 19 | 2011-04-06 | 1.651 | 0.050000 | 7 |
| 20 | 2011-04-07 | 1.609 | 19.997397 | 1 |
| 21 | 2011-04-08 | 1.243 | 8.384303 | 1 |
| 22 | 2011-04-09 | 1.503 | 19.075066 | 5 |
| 23 | 2011-04-10 | 1.992 | 24.617565 | 5 |
| 24 | 2011-04-11 | 1.992 | 25.823411 | 5 |
| 25 | 2011-04-12 | 1.989 | 20.989643 | 4 |
| 26 | 2011-04-13 | 1.440 | 16.216522 | 7 |
| 27 | 2011-04-14 | 1.529 | 9.217374 | 5 |
| 28 | 2011-04-15 | 1.517 | 13.281242 | 4 |

| | | | | |
|---|---|---|---|---|
| **29** | **2011-04-16** | **1.363** | **7.537155** | **2** |

1 -The statistical measures of quality were as follows:

| | |
|---|---|
| **MSE:** | **0.19** |
| **MAE:** | **0.34** |

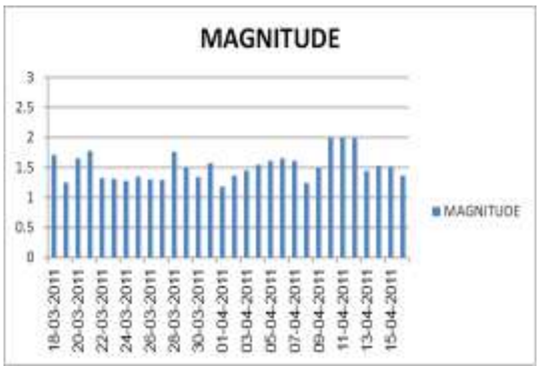


Figure 4: Graph of earthquake strength during the forecast period after the optimization process

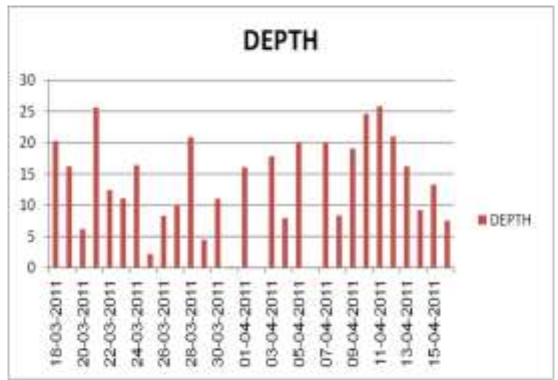


Figure 5: Graph of earthquake depth during the forecast period after the optimization process

| | Before improvement | After improvement |
|---|---|---|
| **MSE:** | **0.2** | **0.19** |
| **MAE:** | **0.38** | **0.34** |

Comparing the statistical model quality measurement tools in both cases before and after the optimization process, we find the following:
1-The MSE scale after improvement became lower than before improvement.
2-The MAE scale after improvement became lower than before improvement.

This indicates that the model after the optimization process has become more accurate in giving predictions. And it became more suitable for dealing with data

Table No. 4 shows the frequency of earthquakes in the regions.

| LOCATION | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| Before improvement | 7 | 2 | 1 | 5 | 2 | 8 | 4 | 0 |
| After improvement | 6 | 6 | 0 | 3 | 7 | 2 | 5 | 0 |

Figure 8: Map of the Syrian coast and expected earthquake locations after the improvement process

## 7.Conclusion

1- The Markov chains method was able to predict earthquake events.
2- The model was found to be more accurate and predictive after being improved using AI techniques.
3- It would have been possible to obtain predictions for longer periods, but the lack of data prevented this.
4- If more data is available, more accurate AI methods such as neural networks can be used to improve the performance of Markov chains.
5- It turns out that most earthquakes occur with a magnitude ranging between 1 and 3 on the Richter scale, and in rare cases, surges may occur that may reach more than 3 on the Richter scale.
6- It was found that the depths of most earthquakes that occur range between 1-25 km underground, and rarely exceed 30 km.
7- The results showed that the most frequent earthquake areas are the fifth area, then the first and second areas before the improvement process. As for after the improvement process, I thought that the most frequent earthquake areas are the sixth area, and this is logical because it is geographically close to the fifth area, followed by the first area, which was also one of the most frequent earthquakes before the improvement process.
8- It was found that there is a clear difference in the results, for example, in the number of earthquakes in different regions or the strength of earthquakes. This reflects a discrepancy in the accuracy of the two models. The first method may be more sensitive in some regions, while the second method may be more accurate in others. Furthermore, the difference in results between the two methods is due to the difference in the methodologies used for prediction. The first method relies on Markov chains, while the second method relies on machine learning. Therefore, the difference is natural due to the differences in the mathematical methods and assumptions used.

## 8.Recommendations

It is recommended that information on earthquakes and tectonic plates be provided to researchers by institutions concerned with this field.

1- increasing the guidance of researchers to study the statistical methods used in prediction and which can be improved by artificial intelligence methods and apply them to many research fields..

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## إيجاد التنبؤ الأمثل بحدوث الزلازل باستخدام سلاسل ماركوف وأساليب الذكاء الاصطناعي

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**الخلاصة:** يُقدم هذا البحث منهجيةً للتنبؤ بالزلازل، حيث تمت دراسة البيانات الزلزالية للمنطقة الساحلية السورية للفترة من عام 1996 إلى عام 2011، والتي تضمنت قوة الزلزال وشدته وموقعه وتاريخ حدوثه. في ضوء تحليل هذه البيانات، تم تحديد منهجية للتنبؤ باستخدام سلاسل ماركوف لفترة محددة. بعد ذلك، تم تحسين هذه العملية باستخدام إحدى مناهج الذكاء الاصطناعي، وهي أسلوب التعلم الآلي باستخدام أسلوب الغابات العشوائية. ونتيجةً لهذا التحسين، تم الحصول على دقة أعلى في النتائج. يقدم البحث نهجًا متقدمًا للتنبؤ بالزلازل من خلال دمج تقنيات الذكاء الاصطناعي مع سلاسل ماركوف، مما يؤدي إلى الحصول على تنبؤات مقترحة تُمكّن المجتمعات من اتخاذ تدابير وقائية أفضل وإزالة المخاطر عن السكان. وهذا سيؤدي إلى تقليل الخسائر في الأرواح والممتلكات والبنية التحتية قدر الإمكان. وهذا هو هدف جميع الدراسات المتعلقة بالتنبؤ بالزلازل في العالم وبجميع أنواعها.

**الكلمات المفتاحية :** الزلازل ، سلاسل ماركوف ، احتمالية الانتقال ، الذكاء الاصطناعي ، الغابات العشوائية .