RESEARCH PAPER

Predicting spatiotemporal changes in Iraqis Displacement shelters.

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A B S T R A C T:

Iraq is a country well known for having a lot of problems and open conflicts. After a century of wars and growing political rivalry, there are still a huge number of refugees and internally displaced people (IDPs) in Iraq. According to the United Nations (UN) guiding principles, IDPs are people who are forced to leave their places of habitual residence and move to another place. They didn't cross internationally recognized borders but still can't return to their homes. After the crisis in 2014, the number of IDPs in Iraq rapidly increased, reaching 6 million, with the loss of their livelihoods, employment, and source of income from their place of origin. The issue we are addressing in this paper is predicting the next changes in the IDP population in each governorate among different shelter types. To have an advance and clear vision of the next changes regarding humanitarian aid, deliver humanitarian aid in advance, analyze return barriers faced by IDPs, distribute the limited funding available by UN organizations, and define which areas of emergence need more attention. This study aims to find a suitable model for predicting a future change in the IDP population while a limited amount of data is available. As a result, a new model called recurrent neural network distance (RNN_Distance) was proposed, consisting of a combination of traditional recurrent neural network (RNN) and Euclidean distance techniques with 99% accuracy. Also, we compared the result of the proposed algorithm with various existing machine learning models such as decision trees, random forests, linear regression, autoregressive integrated moving average (Arima), and Facebook Prophet (FB Prophet), then discussed the outputs. RNN_Distance was proposed, consisting of a combination of traditional recurrent neural networks (RNN) and Euclidean distance techniques with 99% accuracy. Also, we compared the result of the proposed algorithm with various existing machine learning models such as decision trees, random forests, linear regression, autoregressive integrated moving average (Arima), and Facebook Prophet (FB Prophet), then discussed the outputs.

1. INTRODUCTION:

Iraq is a country well known for having problems and being open to war during the last four decades. The newest and latest was in 2014, when the Islamic State of Iraq and the Levant (ISIL) launched an offensive across northern Iraq. Many of the cities were destroyed during the conflict. Over 6 million people have been internally displaced.

According to the data that has been published by the displacement tracking matrix (DTM) department of the International Organization for Migration (IOM), hundreds of thousands are trapped in camps, informal sites, and critical shelters far from their hometowns.

In this study, based on the few available data points, we are trying to predict with accuracy future changes in all eighteen governorates of Iraq among all different shelters. After applying extensive machine learning and deep learning algorithms and comparing the results to get a suitable model for forecasting small datasets, we

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proposed a new model including the Euclidean distance technique with eight layers of LSTM. With the proposed model, the accuracy of the predicted result increased by 2% compared with a traditional RNN and was generally better than all other machine learning algorithms by at least 10%.

Predicting the total number of IDPs in each shelter is our main goal. The IOM-UN organization collects that data once every three months; since 2018, four rounds per year have been collected, for a total of 20 rounds, as shown in Figure 1. So, in this case, we are dealing with a very small dataset. It means our challenge in this study is finding a suitable model by comparing the results that have been provided by machine learning with the results from deep learning for predicting a better result while you are training a small dataset.

Iraqi IDPs have increased significantly since 2018, and there have been no significant changes in the IDP flow. In this case, we have a trend component in our dataset. A trend is a long-term increase or decrease in the data, and it is one of the components of a time series that makes the prediction harder. As shown in Figure 1, the predicted result rose to nearly 99%. Rather than the Iraqi displaced people dataset, we tried the same new model on the Ukraine dataset shown in Figure 2. But in this dataset, there was a different issue, which was seasonality. Seasonality is another component of time series that makes prediction harder. The accuracy of the result rose from 73% with the traditional model to 78%. The result proved that our proposed model can predict better in both cases when the data has trend or seasonality difficulties.
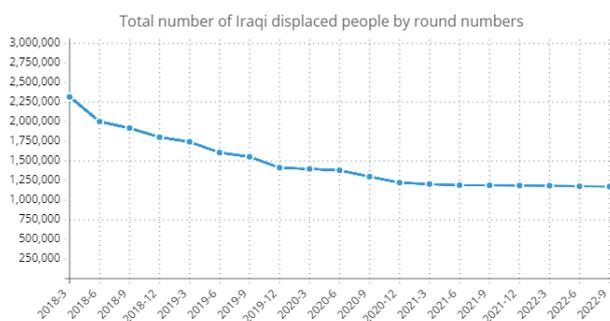

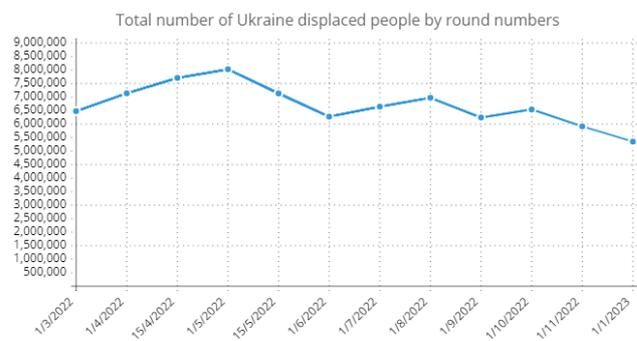**Figure 1:** Total number of Iraqi displaced people by round.

Figure 2: Total number of Ukraine displaced people by round.

At the end, we can list our main contributions as follows:

1. We collected 20 rounds of data on Iraqi Displaced families, split by Governorate and shelter type. On the other hand, 12 rounds of Ukrainian displaced families are broken down by their current geographical location. And analyzed both datasets for the first time.
2. We used the top popular models in machine learning and deep learning techniques for finding a suitable model, which were Decision trees, Random forests, Linear Regression, Arima, FB Prophet, and traditional recurrent neural networks (RNN). We then proposed a new model of RNN.
3. We improve the model's performance more than traditional deep learning models when you have a small dataset.
4. We used a new technique based on RNN models to have the most accurate prediction for future data with small datasets on top of other models, then increased the accuracy of our predicted result.

2. RELATED WORK

Now a day one of the most important machine learning models for time series for casting is FB Prophet (Aditya Satrio et al., 2021). Which is

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developed by Facebook's core data science team. The Prophet model is a combination of Trend, Seasonality function, and holiday effect. (Aditya Satrio et al., 2021) and (Liço et al., 2021) are somehow used as prophets for predicting a future result when a minimum of data is observed. Also (Aditya Satrio et al., 2021) used to predict the number of patients who were confirmed, recovered, or died from COVID-19 between April 22, 2020, and May 21, 2020. 30 days in total. The accuracy of the predicted result was 91% for confirmed cases, which is a very good result with a small dataset.

Arima is another model that we applied to our datasets. As long as Arima is one of the popular machine learning algorithms used for time series predictions, Mainly for the training process with Arima, it needs to have a large dataset so that you can get a better result, as (Liço et al., 2021) used their big data starting from 2004 to 2020 for predicting the change of the next 30 years of ocean warming, which caused migration of fish in shallow waters in the seas near Scotland. On the other hand, (Aditya Satrio et al., 2021) applied Arima to a 30-day period of data. And it does not have a good result.

Also (Yenidogan et al., 2018) as well as conducting research on Bitcoin's future values, they compared the results obtained by Prophet against ARIMA. At the beginning, both performed well in the training and validation processes. They end up predicting their values with Prophet considerably better than ARIMA on their test set. As we get to the same point.

So far, several studies have used Facebook's Prophet Forecasting data. But (Ye, 2019) used Prophet and Arima to propose his own model for forecasting weather changes. And somehow, by using Auto Arima with Prophet, we got a better result than using each of them alone.

(Khonsari, 2018) Preferred to use machine learning and natural language processing techniques in his study to make predictions on forced migration based on news items. To extract violence ratings from news stories, the authors presented two unique techniques: ED-FE and TD-FE. In order to create time-series autoregressive models, they used random forests, neural networks, and linear regression. The models were updated to include the extracted violence scores as input, and the efficiency of the violence scores in raising prediction model accuracy was assessed. Through tests, the authors proved that the discovered scores are useful for foretelling forced migration. Our data was much smaller and couldn't be trained by using linear regression and random forest, and the result wasn't proper to use.

Another popular machine learning algorithm is the Random Forest, which builds several decision trees during training and outputs the mode or mean prediction of the trees. This is a popular ensemble learning technique for classification and regression applications. (Zhan et al., 2021) developed a random-forest-bagging BLS model for predicting COVID-19 spread in 184 countries and 1,241 areas using a training dataset with crucial features and a bagging strategy. In our study, we used random forests to train the total number of IDP families in each shelter before predicting the next changes in the same shelter. Using a random forest model wouldn't be a good idea when you have a small dataset.

Then (Fang et al., 2021) confirmed that last year's many researchers tried to take advantage of deep learning algorithms in many areas, one of which is forecasting. (Fang et al., 2021) use RNN-based CNN for predicting spatial and temporal data. They captured the features by using CNN and then predicted the time series data using RNN. In addition, they really focused on separating the spatial and temporal data, then applied two different mechanisms for getting the predicted result.

(Palangpour et al., 2006) used RNN as well for predicting elephant movement in South Africa. The dataset was collected between the periods of 2000 and 2002 and then divided into two separate rounds, each of which had a separate trainer. The training process has been successful to some degree, but (Palangpour et al., 2006) do not propose using the networks as the model did not work well with the amount of data used in the training process. As it happens in our research, we trained on Ukraine datasets, which are quite smaller than Iraq datasets. But we got a better result with our RNN model.

In order to estimate upcoming international migration to 35 OECD nations,(Golenvaux et al., 2020) proposed a new five-layer LSTM technique mixed with linear gravity and ANN models when paired with Google Trends data and using a large amount of search query data from Google. This

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implies that machine learning techniques, such as the LSTM approach, may offer a major improvement over current approaches for understanding migratory dynamics. Predictions. However,(Golenvaux et al., 2020) could improve the accuracy of migration and suggested it might be a significant alternative to conventional methods for researching migration movements. And the difference with our study is that we are facing a lack of data for the training process.

In order to calculate the HIV incidence in Guangxi, China, (Wang et al., 2019) studied different types of algorithms such as LSTM, ARIMA, GRNN, and ES models. Then improves a new LSTM model, which made used huge historical dataset from 2005 to 2014. The model with the lowest MSE was chosen as the best one. Even with that amount dataset (Wang et al., 2019) prioritize using LSTM model over all other models because LSTM was more predictive than used models, making it essential for keeping track of and managing the Guangxi HIV a global epidemic.

As we mentioned before, one of the challenges in our study is finding the best model that can be predicted well with a small dataset. RNN is one of the deep learning models that can be customized according to your dataset. As with other models, having a large dataset for training will give you a better result, but RNN can also be used with small datasets (Panda & Majhi, 2021) and still provide an accurate result. (Panda & Majhi, 2021) showed RNN has been used for predicting protein structural class, getting 85.36%, respectively, by applying it to a small dataset.

On the other hand,(Abrishamkar & Khonsari, 2019) use a massive dataset of 680,000 samples of migration data to propose a new model for forecasting population displacement based on violence scores and other features. (Abrishamkar & Khonsari, 2019) focuses on applying many techniques, including LSTM, GRU models, LSTM2LSTM, random forest, linear regression, support vector regression (SVR), stochastic gradient descent (SGD), and multi-layer perceptron regression (MLP). The SGD regression model performs well in terms of RMSE and is suggested for use as a regression model for prediction. The UNHCR dataset used in the paper is a subset related to Iraqi and Syrian refugees.

80% of the data from 2012 to 2016 is in the training set, while the remaining 20% from May 2016 to April 2017 is in the test set.

(Nasir & Ahmed Hamdan, 2021) used Neural Networks (RNN) as a type of Artificial Neural Networks (ANNs) to evaluate the performance of RNN in drought forecasting in Iraq. RNN is a non-linear ANN that re-inputs model outputs. He used historical drought data for Iraq from 2020 to 2030. The results revealed that Iraq was experiencing a range of drought conditions, from minimal to extreme. Improvements were achieved, but more funding is still needed to reduce the drought condition for 2020–30. The study examined the occurrences of drought at 24 meteorological stations between 1950 and 2016. We believed it had a good result based on that amount of data.

RNN with intense structures of layers that go deep and deep can provide a good result when there is a massive dataset such as that developed by (Bae & Aoga, 2020) for multivariate migration intention forecasting. 50 layers of LSTM for training seven years and eighty-four months of data However, with a small range of data, it is better to keep the number of neural network layers lower than (Bae & Aoga, 2020).

Finally, in this study, we are comparing the most popular machine learning and deep learning algorithms that can be used for forecasting with a small dataset. Then another challenge is finding a bridge between machine learning algorithms and deep learning, so that can be a new approach in that area for having an accurate result.

3. METHODOLOGY

The methodology used in this work comparing a variety of machine learning methods, including Decision Tree, Random forests, Linear Regression, Arima and FB Prophet, to estimate changes in shelter occupancy. For the purpose of recognizing temporal patterns, a proposed LSTM model with Euclidean distance computation was also created. The flowchart of working flow presented on Figure 3.The process break down into below crucial steps.

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3.1 Dataset

3.1.1 Data Collection

This study used data from the Iraq Displacement Tracking Matrix (DTM) website, which provides a comprehensive dataset on the population of internally displaced persons (IDPs). The data collection process involved accessing relevant sections and extracting necessary information for analysis. The website is considered a reliable source of information on displacement patterns in Iraq, offering extensive data on IDPs and their living conditions. We collected the data on our website. Including five years of data from 2018 to the end of 2022, four rounds per year, and 360 samples of row data in total.

3.1.2 Data Analyzing

The dataset contains information about shelters and residents. There are eighteen governorates in Iraq (Anbar , Babylon, Baghdad, Basra, Dahuk, Diyala, Erbil, Kerbala, Kirkuk, Missan, Muthanna, Najaf, Ninewa, Qadissiya, Salah al-Din, Sulaymaniyah, Thi-Qar and Wassit).With identifying fifteen type of shelters in each governorate which are listed on Table 1 .The total number of IDP population is always changing with in each governorate each shelter. It might be increasing, decreasing or stay the same. Predicting the next change will lead national, international organizations or authorities to plan for protecting and assisting them also to find solutions that allow them to rebuild their lives earlier.
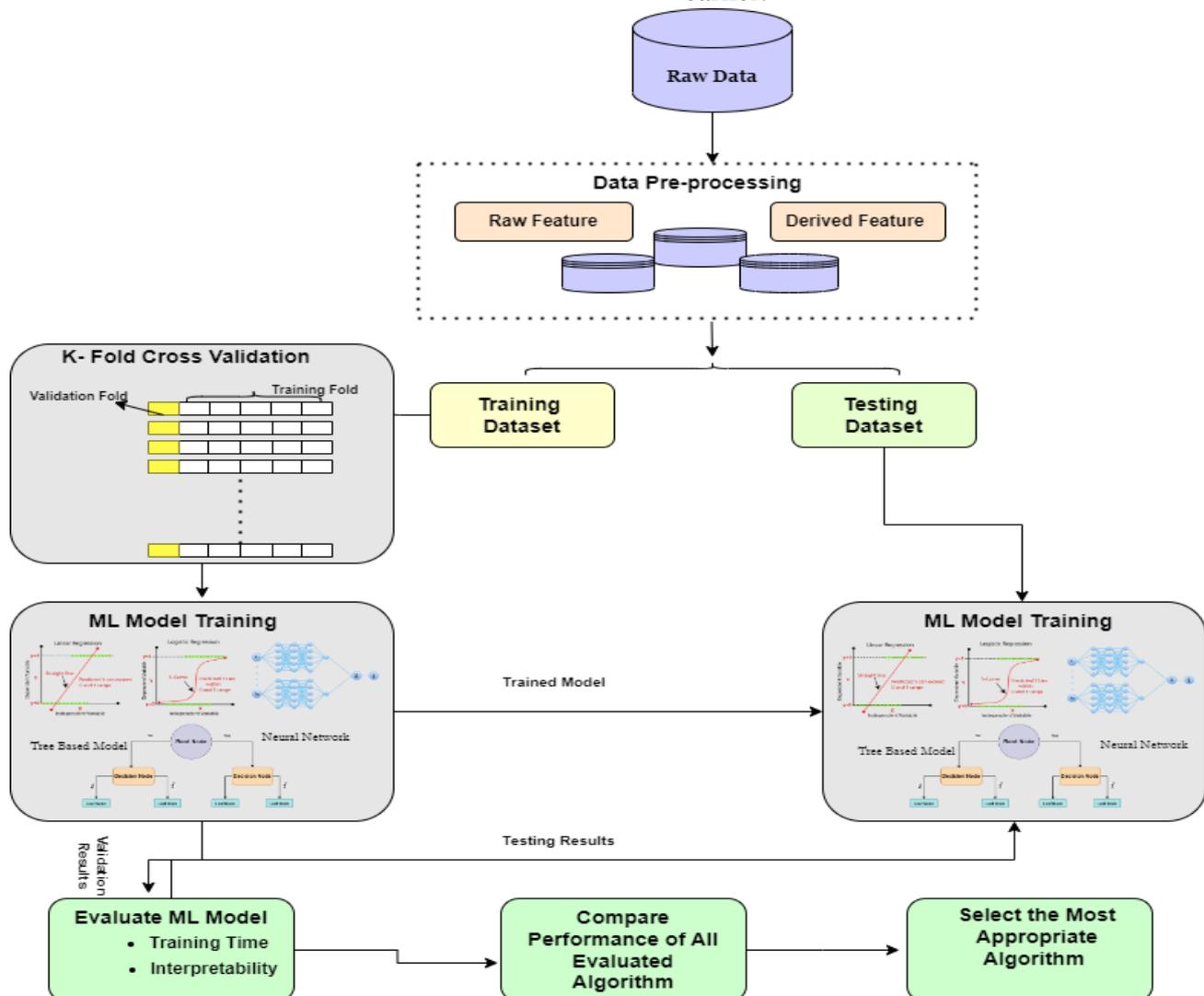

Figure 3: Flow chat of Methodology

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3.1.3 Data Preprocessing

A dataset with too many relational and different features can't be used in the learning process, while for a dataset like this, only the most useful and related attributes have to be selected (Alexandropoulos et al., 2019) . So, to have only useful information, it is important to reduce information that is unnecessary and unrelated to our study. A set of features has been used in our studies: the total number of IDPs in each governorate and the total number of IDPs per shelter type have been selected as well. As shown in Table 1, a list of necessary and related data has been selected with discerption. The data was preprocessed using a number of approaches, including hyphen removal for consistency, forward-fill and backward-fill methods for filling in missing values, managing zero values using Euclidean distance calculations, and label encoding for converting categorical data to numeric representations.

Table 1. List of related information has been selected.

Features	Descriptions
Governorate ID	Unique ID number for each Governorate
Round Number	Round number of data gathering
Month	Month recording data
Year	Year of recording data
Latitude	Geographic latitude
Longitude	Geographic longitude
Camp	Shelter type
Informal Shelters	Shelter type
Unfinished Building	Shelter type
Religious Building	Shelter type
School Building	Shelter type
Public Buildings	Shelter type
Other Critical Shelter	Shelter type
Rented Uninhabitable	Shelter type
Rented Housing	Shelter type
Host Families	Shelter type
Renter Habitable	Shelter type
Hotel or Motel	Shelter type
Own Property	Shelter type
Unknown Shelter	Shelter type
Other Shelter	Shelter type

3.1.4 Splitting the dataset:

While the learning process depends on the data itself, we have to find a good balance to avoid overfitting the data (Gholamy et al., 2018). We splattered our data into five groups labeled by their years (2018, 2019, 2020, 2021, and 2022). Then, for each year, split 75% of dataset D into the training set D_train and 25% into the testing set D_test to evaluate model performance and generalization. In this case, our models will use three rounds of data as training, then predict the fourth round, and a yearly prediction will be achieved.

3.2. Proposed Long Short-Term Memory (LSTM):

In this work, a unique technique has been proposed to enhance the performance of the LSTM model and include extra information. For the dataset's temporal linkages and trends, we included a Euclidean distance computation. This improved LSTM model, known as our Proposed LSTM Model with Euclidean distance Calculation, uses Euclidean distance to learn more complicated temporal patterns while taking into consideration the historical sequence of features.

The Euclidean distance calculation has been applied to the data to find a new set of inputs that consist of the calculation between rounds, then reshaping the data by (-2, 1). After that, both the original data, which has been reshaped by (-1, 1), and the new value, which is the result of Euclidean distance, will pass through the training process. In this case, we are using multiple inputs to train the process. The size of the dataset remain the same but the model will be trained on a couple of inputs instead on only one input for each shelter type. The model will train better than a traditional model with the same number of layers. The main difference with traditional RNN is that it increases the number of input values that have been extracted from the origin input values themselves. The LSTM model can more accurately reflect fluctuations and relationships between subsequent time steps by including the Euclidean distance computation, which enables it to forecast shelters for subsequent time steps with greater accuracy.

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We believe having an intense and deep model with a massive number of layers may provide us with a closer result to reality. We tried the same proposed model but with different numbers of layers, six, eight, and ten, as presented in Figures 4 and 5. The result is clear: having the same model with 10 layers accomplished a good result as well with 97% of the accreted data with 111 RMSE, but with no doubt, we prefer the model with 8 layers because it is less time-consuming and has a better result with 99.9% accuracy data with the best RMSE, which is 64. We ended up with the result that having a minimum number of layers provided a better result than a deep model with a massive number of layers, even though the data could not be trained well because of the lacks of data in our case.
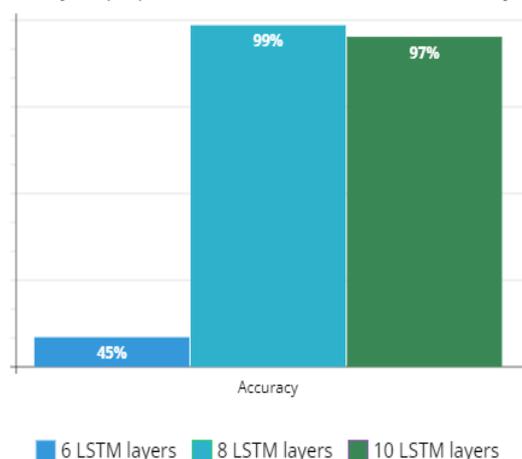

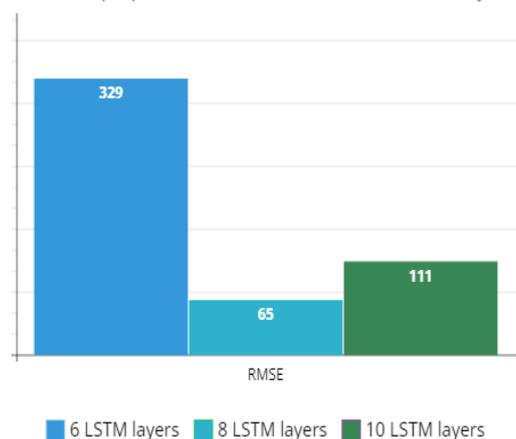**Figure 4.** Accuracy different number of layers.

Figure 5. RMSE different number of layers

In the proposed model, we also used 8 fully connected layers of different sizes, which are 256, 128, 96, and 64).So in this way of structuring the layers, we can cover the issue of lack of data and train our models much faster. Then apply dropout to the output of each couple of layers (LSTM and dense layers) to prevent overfitting of the result. The first time, we dropped out by 0.2, which means ignoring the results that were less than 20% of the predicted data. Then resized both LSTM and dense from 256 to 128 and dropped out the result by 20%. The output goes to another couple of layers in a smaller size, which is 96, and then for the third time we drop out the output, but this time by 5%; the last time was by 1. During the neural network training process, the activation function plays an important role in providing the necessary activation functions, and sigmoid is often one of the most commonly used activation functions in a neural network. By using sigmoid, you can provide the translation for the input range from $(-8; +8)$ to the range in $[0; 1]$. It is non-linear by nature and has nonlinearity in the model so that the ability to learn complexes will be represented. Additionally, we used sigmoid as a smooth derivative as well. Then the Adam optimizer with a learning rate of 0.001 was used as an optimization technique.

3.3 Machine Learning Algorithms

For compering and forecasting shelter occupancy, the study used a variety of machine learning algorithms, including Decision Tree, Random Forests, Linear Regression, Arima, and FB Prophet. The models in machine learning algorithms learn from the data itself; based on some features of the input data, the output can be predicted. On the other hand, making models to learn from past existing data and behave as a human brain, thinking about the result and then predicting the output, is called "machine learning," which is a subset of artificial intelligence.

Arima: This is the first model in machine learning that has been used. Usually, Arima needs a huge dataset for the training process so that you will get an effective result. A linear combination of past values and past errors with the current value of a future variable can be prepared. By training the

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data, which are multivariable predictions by Arima, the accuracy of the total years was 68.88%. In our study, Arima is not suggested to be used while you have a lacks of data and cannot get an accurate result with it.

FB Prophet: FB Prophet is another extensively used model that is powerful and easy to use for predicting time series data. The strangest thing about using Prophet over the other models is that the problems of having a strong seasonality effect in the dataset can be better trained and predicted by FB Prophet. Another reason for adding Prophet was its new and extensive use. The result was an 86% accurate predicted value over all the predicted years.

Linear regression: The third machine learning algorithm was linear regression. Linear regression analysis predicts a variable's value based on another variable's value, with the dependent variable being the predictor variable. As long as we can get a good result by applying machine learning models, linear regression is the same. We got a 77% accuracy result, and as with previous machine learning models, linear regression isn't recommended to use while you have very small historical data.

Decision tree: This is another type of machine learning algorithm that uses a flowchart-like predictive model for regression tasks, dividing data into branches and assigning outcomes to leaf nodes for easy understanding. After training and testing our small Iraqi dataset, the result wasn't preferable to use while dealing with a small dataset. The performance was 77%.

Random forest: the last machine learning algorithm was random forest. A random forest is an ensemble of decision trees, with each tree producing a class prediction, with the most votes forming the model's prediction. We couldn't get the targeted result with it as well.

4. RESULT AND DISCUSSION

4.1 Interpretation for ML models:

In this paper, the outcome of our work is the proposal of a new deep learning model algorithm

(LSTM) with new Euclidean techniques parallel with LSTM layers to predict changes in IDP numbers in each type of shelter for each governorate. We have used the first three rounds of each year as training data and the fourth round as test data. We showed that if you have a lot of data and only a very few rounds of historical data available, you can use this proposed technique to increase the input numbers in the training process. As we increase the input numbers from one to two. The first input was our original data; the second input was the result we got by applying Euclidean distance between rounds of that data. With this technique, the data can be trained better and learn fetchers from the historical data in a proper way with less time consumption, increasing the performance of our output.

However, other algorithms such as Decision Tree, Random Forest, Linear Regression, Arima, and Prophet produced passable results. Table 2 is a comparison of the accuracy of the output by applying five popular machine learning and deep learning algorithms. As a result, we believe that with a small-time series dataset, we can use deep learning models for prediction such as RNN, and additional techniques such as Euclidean distance can make the result much more accurate.

4.2 Interpretation for the proposed LSTM model

We trained the model with our dataset and predicted the next change in shelter in each governorate. We fixed the number of governorates at 18, which is standard for UN IOM. As we got high accuracy with our proposed model by training the IDP datasets in Iraq, we decided to train another dataset in the same area, which was the Ukrainian displaced people dataset, to see if we could get much more accurate predicted data from our model. As shown in Figure 6, the Ukrainian dataset has a much more seasonal and extensively used effect than the Iraq dataset, which had a trend effect. As we guessed, the accuracy of prediction for the Ukrainian time series dataset by using our model increased by 5% compared to using traditional RNN, which raised it from 73% to 78%.

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Table 2. Accuracy of Machine learning and deep learning models.

Models		2018	2019	2020	2021	2022	Overall
Machine learning	**Arima**	81%	73%	48%	89%	53%	69%
	Prophet	87%	80%	93%	83%	91%	87%
	Decision Tree	89%	89%	89%	90%	90%	89%
	Random Forest	91%	87%	91%	89%	90%	90%
	Linear Regression	90%	89%	90%	91%	90%	90%
Deep learning	**RNN-LSTM**	97%	97%	96%	99%	100	97.8%
	RNN-Distance	99%	98%	99%	99%	100	99%

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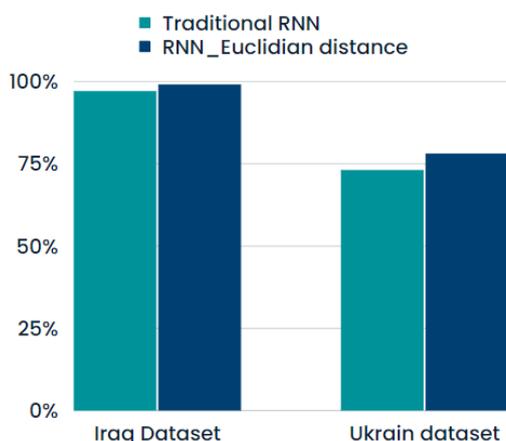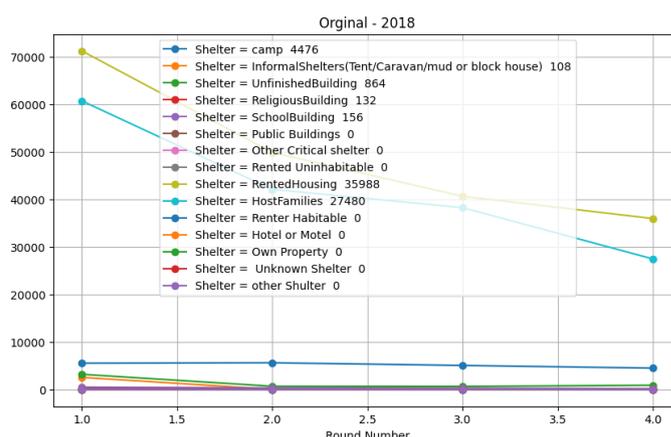

Figure 6: Accuracy of Iraqi and Ukrainian output result with traditional and new RNN technique.

As shown in Figure 7, this is an example of yearly predicting of all shelter types in one of the governorate in 2018, the suggested LSTM model with Euclidean distance calculation exhibits encouraging results. In most of shelter types including (Camp, Informal shelters, Rented House, Host Family, Public building) better than using traditional RNN only and much closer to the origin total number. Also for the shelter types (Motel, Own Property, Renter Habitable, Unknown Shelter, Other Shelter, Critical Shelter and rented Uninhabitable) exact the same.

A) One of the Governorate with origin total number of IDPs in all shelter types for round four

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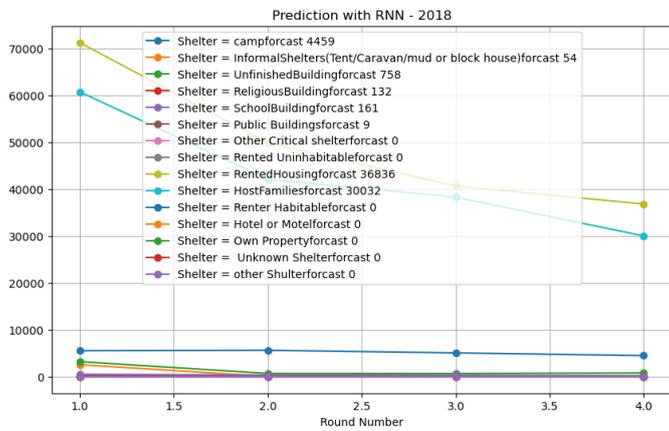
B) One of the Governorate with predicted total number of IDPs in all shelter types for round four by using RNN
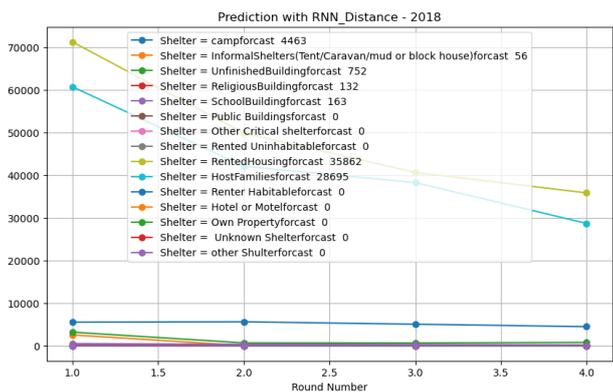
C) One of the Governorate with predicted total number of IDPs in all shelter types for round four by using RNN_Distance.

Figure 7: Example of Origin data on plot A and predicted data by RNN on plot B and RNN_Distance on plot C.

At the end, the proposed LSTM model with Euclidean distance calculation offers a reliable and accurate method for forecasting spatiotemporal changes in informal shelters across distinct governorates. The model's performance demonstrates its ability to support decision-making procedures and provide guidance for policy actions pertaining to shelter management and resource allocation in response to shifting shelter demands.

5. CONCLUSIONS

In our study we comparing five different models in machine learning and deep learning in forecasting while have to predict with tiny dataset. For forecasting the spatiotemporal changes of different shelters in Governorate in Iraqi. The proposed LSTM model with Euclidean distance computation performed remarkably well. According to the results, this model performed better than other machine learning algorithms such as Decision Tree, Random Forest, Linear Regression, Arima and Prophet, as well as the deep learning method LSTM without distance computation by 2%.The Proposed LSTM model's improved performance is further supported by its low Root Mean square Error (RMSE) values. The low RMSE values imply that the model's forecasts are quite precise and closely match the actual shelter types. The Euclidean distance computation was incorporated into the Proposed LSTM model, which enabled the model to successfully capture spatial patterns and connections across shelter classes. By understanding the dynamics of shelter types in various governorates, policymakers may develop and put into action preventative measures to overcome potential barriers and offer a more effective response during crises or circumstances involving displacement.

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