Application of Deep Learning in Tourist

Daniel Samwel Makala[a] and Li Zongmin Li[b]
Department of Computer Science, China University of Petroleum (East), Qingdao, China

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Abstract: One of the Giant sectors in Tanzania is Tourism. About 40% of the foreign exchange in Tanzania comes from this sector. It is the number one job provider to Tanzanians, about 10% of the working class is in the tourism sector. Since independence, the sector has been growing well until 2019 during the pandemic issue of COVID-19. However, since 2020 Tanzania has regained and restored the tourist income to normal and expected more tourists. Government and Authority are in the age of determining the number of tourists to come and the income associated with the tourist for better planning. Forecasting tourist inflows requires an accurate model because of the highly changing tourist data due to external factors such as political influence, security issues, or transportation issues. This study analyses and proposes the CNN to be used for the prediction of tourist arrival. CNN can handle and process multiple sequences and thus can handle data and multivariate time series. Using data from 1961 to 2022, of Tanzania's arrival, the proposed model was able to predict with more accuracy compared to ARIMA, LSTM, and CNN-LSTM by having 0.1 RMSE. However, the study is limited due to the unavailability of daily tourist income.

1 INTRODUCTION

1.1 Overview of Tanzania Tourism

Tanzania is one of the most beautiful countries in the attraction of visiting and tourism. She is most famous for her natural gorgeous and rich cultural heritage. She is home to the beautiful highest mountain in Africa, Mount Kilimanjaro, and the world's number one natural national park, Serengeti National Park. Not only those two Tanzania has abundant attractions including Zanzibar Island, Ngorongoro creator among many others. Because of this beautiful nature, the demand for quality tourism services has increased. The Tanzanian tourism industry contributes a lot to the Tanzanian economy. It contributes about 17% to the national GDP of the country and 35% of all foreign exchange revenues. According to government statistics, the tourism sector provides direct and indirect employment to the people. It was recorded in 2018 that this sector gave out 2.6 million jobs to the people. This means the tourism sector in Tanzania is one of the major job providers. (Kyara et al., 2022).

It is all known that the pandemic of covid 19 disturbs each economic sector everywhere. This tragedy spared no sector as the tourism sector also faced this challenge. This is because of many countries' restrictions on traveling, and it was predicted that international tourism would fall by 80% (Henseler et al., 2022). Before COVID-19, this sector was the leading foreign exchange earner in Tanzania. From late 2021, the sector is regaining momentum, and the government has to lift the sector to its peak. One of the ways used by the government is the introduction of the royal tour (*Tanzania Tourism Sector - February 2023 Update*, n.d.). The royal tour involves the President of Tanzania as the tour guide. The president's ultimate guide for a week, unveiling Tanzania's history, environment, music foods, and culture, as well as telling the stories of Tanzania's hidden jewels. The CEO of the Hotel Association in Tanzania said We hold better positive projections in 2023. If the income of tourists increases at this rate, then we can call it a full recovery at least by the end of this year (*Tanzania Tourism Sector - February 2023 Update*, n.d.).

With the increase in popularity, it comes with the responsibility as it is very crucial to manage the

[a] https://orcid.org/0000-0003-3827-2346
[b] https://orcid.org/0000-0003-4785-791X

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number of visitors entering the countries to maintain better environments for the attractions as well as to ensure the environment is not damaged or overwhelmed by tourists. Thus, it is essential to determine the volume of people (tourists) visiting the country over time. Forecasting the income of tourists will enable stakeholders in the tourism sector to provide a memorable experience for their tourists and hence a country gets better recommendations to attract more tourists. A better prediction model is needed.

This study uses the Tourism sector in Tanzania as a case study as Tanzania is one of the countries doing better in the tourism sector. This case study will represent the tourism sector around the world.

1.2 Background of the Study

As discussed in the earlier segment, it is important to forecast the number of tourist arrivals in any country for better tourism service. This article focuses on identifying the best deep learning model to be used for forecasting the volume of tourist arrivals with the case study of Tanzania. Nevertheless, the study also engaged in comparing the results of the proposed model with the real data to see how the model has performed. Lastly, the study uses the model to focus on the volume of tourist arrivals in Tanzania.

In this study, the deep learning mole is considered since deep learning has been showing a greater impact in the prediction analysis of times series. The CNN model is proposed to be used in the prediction of tourism arrival in Tanzania. The CNN model has been performing wonders in the health sector, especially in image recognition and speech recognition. Because of the better performance of the model in images, the study proposed this model to use the features in the models to capture the trend movement of the tourism arrival, as it is known the nature of the number of tourists is very volatile and non-linear. Therefore, the proposed model will be a suitable model for capturing all the trend movement of time series data such as the number of income tourists. The proposed model will be compared with another popular traditional model of ARIMA and Deep learning models of LSTM as well as CNN-LSTM models.

2 RELATED WORKS

2.1 Introduction

Related work is simply a summary of existing research and study published materials related to a certain topic. It gives out what some researchers have done about that specific topic. It also provides more sources of information for easy understanding. This part of the related work surveys the available literature to identify current trends and gaps in knowledge, while also providing context for future studies. Different studies have indicated that the way of forecasting is categorized in two ways which are linear way and non-linear ways. (Y. Li & Cao, 2018). However, according to, there are three ways of forecasting, these are time series way, Artificial intelligence, and economics. But time series and econometric ways are sometimes known as traditional ways.

For a long time, prediction and forecasting have been conducted. In previous years linear methods were highly used although they were not able to capture all the non-linearity data for prediction. Sometimes complex models may not perform as perfectly as simpler techniques. (Choy, 1984). "Because of the influence of external forces such as public health, economic crises, and seasonal variations, the tourism arrival time series data have become more complex, and nonstationary as a result, it is tremendously challenging to obtain satisfactory results when dealing with the prediction of such dataset" (Goh et al., 2008).

Different researchers and academicians have discussed the tourism sector in Tanzania. Much more the discussion is based on how tourism employs Tanzanians. It is found that about 5% of GDP is from the tourism sector and this is incline in future time. The tourism sector provides 10% of the working population in Tanzania. The sector is a leading sector in contribution to foreign exchanges. (Wamboye et al., 2020)

2.2 Traditional Forecasting Models

ARIMA method has been extensively used in prediction and forecasting. This model can take into account seasonality variation and that is often used in the tourism sector, since one of the factors that affect the income of tourists is the season of the year. Take the example of (Bumthang, 2018), who researched forecasting international tourists visiting Bumthang in Bhutan. The data used are from January 2017 to June 2017. The out of their research shows that Season Arima (0,0,0) *(1,1,0) performs very well with an accuracy of 91%. More to that (Petrevska, 2017) also conducted a study using 58 observations of the data arrival to Macedonia from 1956 to 2013. The result shows that the ARIMA (1,1,1,) is suitable for forecasting tourists in Macedonia and predicted that by 2018 the arrival of tourists will increase by 13.9%.

Besides the ARIMA model, the economic method known as the Vector Autoregressive model (VAR) is another prediction technique that is doing very well. The VAR model relies on one element depending on the other element. This implies that, to perform with VAR two or more variables are needed and must relate to each other. (*Vector Autoregression (VAR) - Comprehensive Guide with Examples in Python - Machine Learning Plus*, n.d.). This model has been used in tourism demand by different researchers, (Witt & Witt, 1995; Wong et al., 2006).

(Choy, 1984)“Conducted and investigated a comprehensive method for tourism demand analysis. This accurate and systematic approach is based on the Bayesian global vector autoregressive model (BGVAR). They deal with the income of international tourists in nine Countries of Southern Asia.” The outcome of their research shows BGVAR to perform better than the other three different VAR models. They conclude by outlining the superiority of their model and how powerful it is in forecasting tourism in Asia and time series in general.

It is true many studies show wide usage of traditional models, this indicates how powerful ARIMA is among the traditional. (Huang & Min, 2002) And in studies on the demand for tourists in Taiwan. (M. Li et al., 2023) Among others, all show how the ARIMA model is successful, but the model performs well when dealing with the linearity of the data only. Similarly, the VAR model to predict the flow of tourists in Macau, Germany, and British forecasted demand in Greece, and forecasted tourism ex-port and export price of the EU-15, respectively. All the above researchers found VAR to be the best model. However due to the complexity and large volume of data available now days Deep learning has become a solution for the problem of non-linear data. Different traditional models have been used in tourism sectors such as elaborated by (Astuti et al., 2018; Yue et al., 2017).

The traditional models have some weaknesses that lead to the development of artificial intelligence models especially deep learning modes. These include reliance on historical data and linear models, falling short of capturing the complexities of the modern world, failure to capture the non-linear relationship of the variables as well as failure to handle large volumes of data.

2.3 Deep Learning Models

Artificial Intelligence can be defined by dozens of definitions. Some research explains (AI) Artificial intelligence as the power of computers and machines to impersonate the problem-solving and decision-making capabilities of the human mind. (*What Is Artificial Intelligence (AI) ? | IBM*, n.d.). AI is where the world is and deep Learning is the feature. The tourism sector also heavily applied DL techniques in different ways. (Kontogianni et al., 2022). For a better plan of tourist policy, accurate tourism demand forecasting plays an important factor. However, making predictions about tourism is very complex and not in linear form. And here is where Deep Learning Models come in.

(Essien & Chukwukelu, 2022) In their study, the aim is to “provide an efficient evaluation of the existing literature on the applications of deep learning (DL) in hospitality, tourism, and travel as well as an agenda for future research”. Their study is based on a review case analysis. Their study concentrates on the five years of data from 2017 to 2021, basically journals from Springer, Science Direct, Emerald Insight, and Wiley Library. They found out that “Deep learning is mainly used to develop novel models that create business value by forecasting (or projecting) some parameter(s) and promoting better offerings to tourists”.

Other researchers proposed a hybrid model of SARIMA-CNN-LSTM intending to forecast the tourist demand using daily data. Here SARIMA captures the linearity of the data structure, CNN captures nonlinear data features and LSTM captures the long-term dependencies in the data. Combining all these three models ensures they capture every feature of the data. The results show the proposed model of the SARIMA-CNN-LSTM has greater forecasting accuracy compared to the individual model. We all know forecasting the flow of tourists is at an important level for the government and authorities. (Y. Li & Cao, 2018) uses LSTM to predict the flow of tourists where the proposed model performs better than ARIM and Back Propagation Neural Network (BPNN). More to that, (Wu et al., 2020) whose study aimed at forecasting the daily arrival of tourists in Macau China, proposed to use the hybrid mode of the SARIMA-LSTM approach. The results indicate the hybrid model performs well. Again (Chang & Tsai, 2017) compare the SVM, NN and Deep learning applied neural network, by using the MAPE as a measurement of performance they find deep learning applied Neural Network has a MAPE of 2.05% while the other models have a MAPE of 10%.

However deep learning models have resolved the issues raised in traditional models. As we all know nothing is perfect, the deep learning models have some shortcomings too which include that, they perfectly work well when a large dataset is involved. Also, the algorithm of DL models is much more complex. To try to resolve these issues the study uses the CNN model to ensure the mentioned issues are resolved with the main focus being to get the greatest model in the prediction of tourist arrival.

3 METHODOLOGIES

3.1 Introduction

The emphasis of this study is to find the best model for the prediction of tourist arrival using the case study of Tanzania tourist arrival. To achieve this target, the deep learning model of CNN is proposed since the model has been doing an amazing job in various tasks such as image recognition, playing complex games, car-self driving, and speech recognition. The model is then compared with ARIMA, LSTM, and the hybrid model of CNN-LSTM. There here our proposed model together with comparison models is explained in the methodology section.

3.2 Data Collection and Processing

Making predictions about tourism is very complex and not in linear form. And here is where Deep Learning Models come in. One of the key aspects of any research study and to have data. The data may be collected from different sources such as interviews, questionnaires, captured from different platforms, or even face-to-face conversations depending on the nature of your study. Due to the high increase in the usage of technology, and the availability of large volume data, many companies and government institutions put most of the data over the internet (soft data). This paper uses data obtained from the Tanzania National Bureau of Statistics, World Bank, and Statista. (*Tanzania Tourism Sector - February 2023 Update*, n.d.), (*Tanzania: Number of Tourist Arrivals 2015-2022 | Statista*, n.d.). The annual data of tourist arrivals from 1961 to 2022 is obtained from the mentioned websites.

After acquiring the data, the cleaning of the data phase follows. Here understanding what kind of data is needed in our model is required. Cleaning and data processing involve putting the data in the required form, ensuring no missing or filling up of the missing data, and so on. Thereafter data are categorized into training data and testing data. Training data in this study case are the tourist arrival in Tanzania from 1961 – 2012 and the validation data is for ten years from 2013 -2022.

3.3 Convolutional Neural Network

Convolution Neural Network is a deep neural network that has been very famous in image classification, and image search among others in the same line. Because of that, it has been very useful in health centers, especially in cancer detection and MRI scanners. Nerve the less in recent years it has been involved in time series prediction.

CNN structure has two sections, the first being the convolutional and pooling parts and the second party is fully connected layers. The first section, convolutional and pooling consists of an input layer and convolutional kernels. 'The pooling part does a reduction of the dimension and puts them into a single neuron. The convolutional layers perform convolution operations on the time series of the preceding layer with convolution filters" (Luo et al., 2019). The fully connected layer is simply one neuron in one layer that has a connection to another neuron in another layer. It is simple MLP. The fully connected layer is connected to the output layer. Figure 1 explains the structure of CNN. In CNN the number of training weights is small causing a more efficient model and expecting more accurate and reliable results.

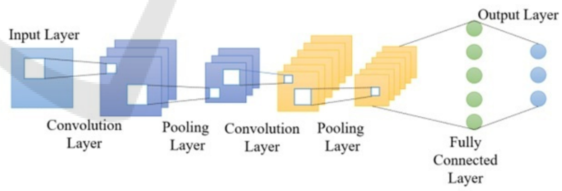

Figure 1Simple Architecture of CNN Model (Gu et al., 2019)

3.4 Long Short Time Memory

It is an updated recurrent neural network that has the capability of learning order dependence in a time series sequence. This means LSTM is a modified RNN that has been explicitly designed to avoid the long-term dependency problem, which is the main issue in RNN models. The LSTM was first discovered by Hochreiter and Schmidhuber to address the issue of long-term relief (Hochreiter & Schmidhuber, 1997)

LSTM uses artificial neural networks. The networks have connections to each other as data can be transferred backward and forward. These neural networks are also known as RNN (Recurrent Neural Network). The structure of the LSTM is comprised of four main sections in a single unit of LSTM architecture. These four components are a cell, an input gate, an output gate, and a forget gate. Three gates control the flow of information into and out of the cell, and the cell keeps track of values over an arbitrary period as described in Figure 2.

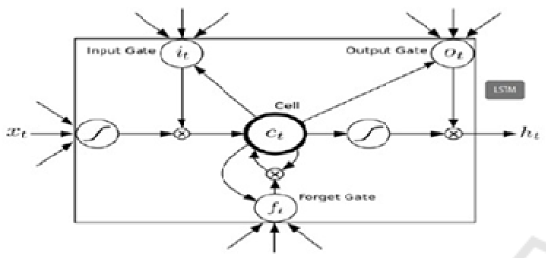

Figure 2 Simple Block of LSTM (Makala & Li, 2019)

Forget gate: As the name expresses itself, the forget gate is in control of determining which data from the previous state is eliminated or kept. This allows the LSTM to have the ability to keep the long-term dependencies. This means forget gate assists in choosing which past information is still important for the prediction and which ones are not important. The data from the previous state meets the current input and are both processed through the sigmoid function where the output is based on 1 or 0 values. For that case when output is zero (0), that means the LSTM forgets that information while the 1 value is kept. Mathematically the work at Forget gate can be expressed as in an equation 1 given that ht-1 is the information from the previous cell and xt is the current input.

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \quad (1)$$

Input gate: One of the gates in the LSTM block is the input gate. It does deal with determining which information is to be added to the cell at a particular time. The input gate has a layer that uses a function known as sigmoid, whereby the sigmoid function generates values between 0 and 1 and these values are the ones that act as gate and control the information passing through. Therefore, the main function at the input gate includes controlling the information entering the cell state, by filtering the important information to pass through and discarding the irrelevant information. In addition to that, there is tanh function which creates a vector of new input that could be added to the cell. More to that, the input gate can handle long-term dependence. Now let the information from the previous state be denoted by $ht{-}1$ and current input xt. The general equation at the input gate will be as:

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \quad (2)$$

Memory Cell: it comprises the CEC, having a recurrent edge with unit weight. The current cell state is computed by forgetting irrelevant information (if any) from the previous time step and accepting relevant information (if any) from the current input. Equation here are

$$\bar{c}_t = tanh(w_c[h_{t-1}, x_t] + b_o) \quad (3)$$

$$c_t = f_t * c_{t-1} + i_t * \bar{c}_t \quad (4)$$

Output gate. This is the last part of the block. As its name is the output gate is where the decision to give output or to re-enter again of information is conducted. It controls what information would flow out of the LSTM unit as the output of LSTM. At this gate, the main function is regulating the information that has been processed in hidden layers and becomes the out of the LSTM unit. Also, this gate enables the LSTM unit to learn the complexity of the pattern and hence improve the performance. In a similar manner as in forget get, the input from the past cell is combined with the current input and they pass through the sigmoid function to generate the value between o and 1 and then are multiplied by the tanh function. These two functions can be expressed mathematically as shown in equation 5 and 6 respectively.

$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \quad (5)$$

And the

$$h_t = o_t * \tanh(c_t) \quad (6)$$

Whereby:

it indicates the input gate, ftshows forget gate, ot is the output gate, σ is the sigmoid function, wx indicates weight at respective gates, $ht{-}1$ shows the input from the previous LSTM block, xt shows current input and bo indicate biases at respective gates.

Generally, LSTM does have to do very well in many aspects because of the function it has in each gate. These gates allow better control of information. More of that it consists of memory cell which enables the storage of information. LSTM should be able to handle the long-term dependency. It has done well in natural language processing, image classification, and time-series forecasting

3.5 ARIMA

Autoregressive Integrated Moving Average is also known as ARIMA by most people. It is one of the old and common models in forecasting and prediction analysis. This model was first introduced by G. Box and Gwilym in the 1970s (Liu et al., 2011; Sato, 2013). ARIMA's name comes from the combination of the three models. AR is simply an autoregression method, I stands for integrated and MA is the Moving average method. This means It combines three important components: autoregression, differencing, and MA to capture the trends and patterns in the data. The mode generally advancements the version of the autoregressive moving average (ARMA). It is most denoted as ARIMA (p, d, q), whereby P is lag order, which is simply the number of lag observations included in the model, and d is the degree of difference which is the number of times that the raw observations are differenced, and q is the order of moving average some time known as the size of the moving average window.

These parameters (p,d,q) can change the model when is obtained. The parameter value of zero (0), indicates that that parameter has no use in the equation and the model. This way, the ARIMA model can be developed to perform the function of an ARMA model, or even simple AR, I, or MA models. Consider an example the value of is (p,0,0) then ARIMA becomes equal to AR(p) since d and q have no meaning and values p, d, and q can never be negative.

In ARIMA the predicting equation is constructed as follows. First, let y denote the d[th] difference of Y, which means:

$$\text{If } d = 0\text{; then } yt = Yt \tag{7}$$

$$\text{If } d = 1\text{: } yt = Yt - Yt\text{-}1 \tag{8}$$

$$\text{If } d = 2\text{: } yt = (Yt - Yt\text{-}1) - (Yt\text{-}1 - Yt\text{-}2) \tag{9}$$

$$= Yt - 2Yt\text{-}1 + Yt\text{-}2 \tag{10}$$

According to (*ARIMA Model - Complete Guide to Time Series Forecasting in Python | ML+*, n.d.) the mathematical presented can be put in words and be Predicted

Yt = Constant + Linear combination Lags of Y + Linear Combination of Lagged forecast errors (up to q lags).

Therefore in ARIMA, it is very important to find the value of parameters p,d,q. The value of p can be found by looking at the value of PACF. This is a Partial Autocorrelation plot. PACF is a correlation relationship between the series and its lag. The Value of d can be calculated by looking at several differencing conducted. The aim of doing differencing is to make time series data at the stationary level. If the data given are at stationery that means d =0. The stationarity of data can be calculated by the Augmented Dickey-Fuller test.

3.6 CNN-LSTM

As the name referred to CNN-LSTM, it is the hybrid of the two models of neural convolution network and the LSTM (long short time memory). CNN-LSTM was created for the focus on the time series forecasting issues and to generate text descriptions from sequences of images and videos, but can also accommodate the times series prediction.

This hybrid method is a combination of the CNN model and LSTM. In this model, first, the input data passes through the Convolution layers in CNN to produce the vectors, which are then passed through the LSTM layers to produce output. The aim of choosing this methodology is to capture all necessary information from CNN and LSTM in case one model is missed. Figure 3 explains the pictorial presentation of the flow of data of the model hybrid CNN-LSTM. Thus In this model, the CNN part will also be involved in interpreting the sequence of input data while LSTM will be put together for the forecasting process.

3.7 Performance Evaluation

It is very important to determine how the models have performed and compare them to each other. These performance measurements tell us how best the model is doing and based on these results, decision-

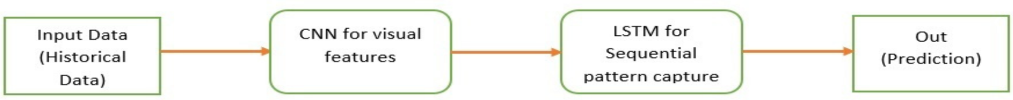

Figure 3 Showing simple flow of data in CNN-LSTM

makers can decide on the different factors to look at when computing the outcome of the deep learning model. For this research work, accuracy was the main factor. Here we consider three main measurement toll that are:

RMSE: This is Root Means Square Error, that simply the square root of the square of different actual values and predicted values it is one of the popular metrics in prediction analysis. RMSE gives the results in the same SI unit as the data used in prediction. For example, in the forecasting of the price of oil, the RMSE result will be in the same price unit. Mathematically:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(predict - Actual)^2}{N}} \tag{11}$$

MAE: This Means Absolute Error is the metric used to measure how much big an error occurred in the forecasting model. Similar to RMSE the results of the MAE are also in the same unit with the value used in the forecasting model.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|Prediction - Actual| \tag{12}$$

R-squares (R2) is sometimes referred to as the coefficient of determination. It is mostly used in a regression model which determines the proportionality of variance in the dependent variable that explains the independent variable. Mostly presented as a percentage value. [46] The higher the value the better performance.

$$R - Squared == 1 - \left(\frac{SS_{reg}}{SS_{Total}}\right) \tag{13}$$

SS_{reg} = sum of squares due to regression, and SS_{Total}The total sum of sq.

4 RESULTS AND DISCUSSION

Before running into the training, the data has to be divided into the training set and evaluation set. Then proposed model is trained with the training in order to learn the movement and trend of the given data. with tunning at different parameters of the model such as different epochs, and the number of layers, the model with epochs of 500 and the 1 convolutional layer of 256 filters provides better results. The outcome of this research article shows that the CNN performed better compared to all other models, however, the hybrid model of CNN-LSTM is also better. Looking at the evaluation tools, the less the value of the RMSE indicates the better performance of the model. CNN model has approximately 0.1 RMSE which can also explain how perfect the model is with R-square, whereas CNN has 99% as shown in Fig 4. Figure 4 shows how results of each model vs the true value. Looking CNN, and True values are very closely followed by the hybrid model of CNN-LSTM

This study expected all of the deep learning to perform better, unfortunately, LSTM did poorly. The main reason of poorly performance of LSTM is caused by having fewer datasets which are annual data. Since the CNN did well followed by the CNN-LSTM, with having r-square of 0.99 and 0.98 respectively, the see pictorial for how they relate with the actual value as shown in Figure 4. If you look over you will observe in both cases the predictions are almost similar to the actual value, however, by looking at the evaluation matrix tools R-Square, RMSE, and Means Absolute Error the CNN did better as indicated in Table 1.

Table 1: Shows the performance of the models.

	RMSE	MAE	R-Squared
	149113.89	133688.35	0.83
ARIMA	408036.81	257622.42	0.26
LSTM	464294.04	389014.22	0.22
CNN	0.09	0.04	0.99
CNN-LSTM	1389	1052.74	0.98

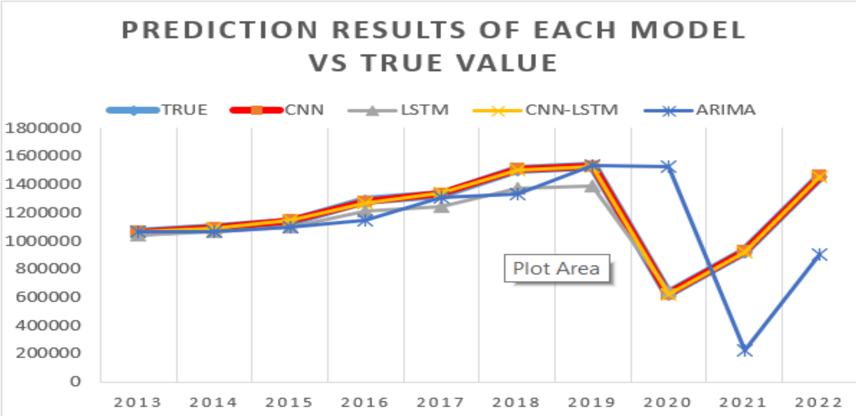

Figure 4 Shows how each model has performed with compared with the true value

5 CONCLUSIONS

CNN has performed well compared to other models. This shows that the deep learning model has more chance of doing better compared to other models regardless of the limited dataset used in this study. Deep learning is the current and future technology since it has already done wonders in self car driven, speech recognition, as well as image classification. The deep learning techniques have the potential to revolutionize the tourism industries across the world by providing accurate information and hence the DL will provide efficient solutions for the market as well as the service provided in the tourism industries. By having the proper framework and designing of the model that can accurately predict customer behaviors and be able to capture the trend of income tourists, the Tanzania tourism sector may have the greater benefit from the increase of revenue as well as improving the customer service to the tourist. More to that Deep learning technology can be used in improving safety levels, within public places through facial recognition logarithms, whereby it helps officials and authorities to keep the cities safe. Also helps against terrorism and hence attracts more tourists.

Nevertheless, the Tanzania government has to overcome and address all the challenges associated with technology adaptation. These challenges include a lack of skilled personnel, technological infrastructure, as well as cyber security. This study believes the Tanzania Government will soon be able to utilize deep learning technology solutions to improve the tourism sector.

In conclusion, this study paper has shown a meaningful input and influence on the tourism sector by forecasting the arrival of tourism in Tanzania. The dataset of tourist arrivals in Tanzania represents all the countries as Tanzania has been used as a place of where the research has been conducted. This study intended to fill the gaps that arise with other models, especially the traditional ones. However, there are some limitations to this research such as the availability of data, thus giving out opportunities for improvements. We further welcome more research to dig more into the application of the Convolutional Neural Network model in the prediction of times series including tourist arrivals.

DECLARATION

The authors of this work declare that they have no known kind of interest that influences this work paper

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