

An Integrated LSTM Neural Networks Approach to Sustainable Balanced Scorecard-Based Early Warning System

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ABSTRACT Developments in the economic environment in the 2000s have become increasingly dynamic and complex. Rapid developments in this kind of economic environment threaten and restrain the sustainability of enterprises. Enterprises need to respond quickly to these burdens and threats to survive and sustain their operations efficaciously in a competitive market in the long run. In order to reduce possible uncertainties in the future and to anticipate economic crises, early risk warning systems should be developed. However, it is seen that management accounting researches are very limited or insufficient on the demand of enterprises for coping with such crises. The aim of this study is to diminish the deficiency in the strategic cost management and prediction of economic crises. Sustainable Balanced Scorecard (SBSC), which was developed as a strategic cost management tool, is constructed in a dynamic way by integrating the early warning system developed for enterprises with an innovative approach into SBSC. Additionally, early warning system model is developed in a manner that successfully predicts economic crises with long short time memory (LSTM) networks using economic macro variables in micro field. As a result of the integration of risk early warning system with SBSC, economic crises will be predicted and necessary strategies will be developed to cope with problems of the crises. Furthermore, predicting economic crises will be turned into opportunities or cause enterprises to make measures with minimum losses. In this model, crisis periods are successfully predicted two crises of 2002 and 2008 with 95.41% accuracy with macroeconomic data between 1998 and 2011.


INDEX TERMS Sustainable balanced scorecard (SBSC), early warning system, economic crises, machine learning, long short time memory (LSTM).

I. INTRODUCTION

Nowadays, as the rapid developments in the internal and external business environment become increasingly complex and dynamic, enterprises cannot respond to these developments too fast. Especially in 2008, the economic crisis posed a constant threat to enterprises [1]. According to James, Wooten & Dushek, the economic crisis causes cash flow problems, reduces existing resources and demand, and also leads to political turmoil [2]. Moreover, it increases the uncertainty in enterprises [3]. Furthermore, it makes the decision-making process and the healthy implementation of management control difficult [4]. In literature, it is argued that the economic crisis affects the functioning of Management

Accounting (MA) and therefore the economic crisis is an important issue that needs to be examined in detail [5]. Although there are important studies on economic crises it is seen that there is little or no study in the way of coping with the economic crisis [6]–[8]. Therefore, new management tools are required for the adaptation of enterprises to the new economic environment and for better crisis management [5].

Zawawi & Hoque argues that the new economic environment forces businesses to adopt innovative MA techniques that need further investigation [9]. Recently, Chenhall and Moers [10] addresses the uncertainty of the external environment and argued that Management Control Systems (MCSs) should include MA Innovations (MAI) to make management control more effective. On the other hand, there have been many studies examining the use of MAI and demonstrating their relationship to economic crises [11]–[13].

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Van der Stede reveals opportunities and threats in MA research in a crisis environment [8]. The study addresses these difficulties by providing information about the impact of the economic crisis and the extent of acceptance and the use of MAI. The periods of economic crises provide unique opportunities for researchers on new research areas compared to periods of no crisis.

Pavlatos and Kostakis report that there were differences between the degree of use of MA tools and the level of importance before and during an economic crisis [14]. They find that, during the crisis, the importance and use of the Operational Costing, Planning and MA tools increase, while the use and importance of traditional cost accounting practices decrease. Most budgeting techniques are still considered significant and are still widely used by many firms.

This study extends previous research in many ways. Firstly, as a new perspective to the SBSC, one of the strategic cost management tools and the prediction of the economic crisis, the economic crisis early warning system is developed and the SBSC is made dynamic before and after the crisis. Previous research has examined the significance and uses of traditional and innovative MA practices at different levels (ie before and during the economic crisis) and identified the differences between them. Another study measured the perception of the intensity of the economic crisis as a new structure and investigated its impact on the acceptance of crisis perception and the scope of the use of MAI [14]. Second, on the basis of macro data, the model developed in this study predicts economic crises using artificial neural networks with a great accuracy of success.

Activity-based costing (ABC) [15], time driven activity based costing [16], target costing [17], Kaizen costing [18], innovative MA tools such as life cycle costing [19], EVA [17] and Balanced scorecard (BSC) have been empirically studied by several researchers [9], [20], [21]. Most of these studies have focused on the underlying features of businesses that influence the adoption of MAIs [13]. It is also claimed that the conditions of enterprises affect the acceptance of MAIs.

The economic crisis is one of the most important reasons for increasing uncertainty for organizations. Accordingly, it is clear that there is a positive relationship between the intensity of the economic crisis and the level of uncertainty experienced by enterprises [22]. Janke et al. showed that the companies most affected by the economic crisis experienced more uncertainty in limited resource allocation compared to the pre-crisis period [23]. This is because it is unclear how customers will decide to allocate their limited income or whether suppliers can manage their orders. As a result, the decision-making process is becoming increasingly burdensome, and more information in better quality is needed [24]. Due to this uncertainty and limited information, it is difficult to predict certain components of the enterprise's business environment. As a result, as the uncertainty in the external environment increases and the future becomes uncertain, more analytical information is needed in decision-making and management control [6]. In other words, companies need better

quality information to manage their goals and fulfill their strategic plans [25], [26].

Hopwood argues that the economic crisis leads to changes in designing of MA Systems that provide better quality of information (more analytical, more precise, and more frequent) to manage economic crises [6]. This information should be taken from both internal and external environments and used to reduce the uncertainty experienced by companies due to the economic crises and to close the information gap. All these show that structures of organizations have become more complex.

Few empirical studies have been conducted in literature, linking economic crises to MA Systems. Initially, Collins et al. find that there is a relationship between the strategy of an enterprise in Latin America and the implementation of budgets in the political and economic crisis and that the economic crisis reduces the benefit of the budgeting system [26]. Reid & Smith also point out that cost management systems are affected by the economic crisis [27].

Janke et al. suggest that there is a relationship between the perception of senior management about economic crises and MCSs [23]. They report that the perception of adverse effects of external economic crises leads to more interactive use of MCSs. Their findings support the positive effect of the interactive use of MCSs on senior managers' perception of negative effects of external crises. In addition, Becker et al. examine the impact of the economic crisis on budgeting. They find that during the economic crisis, budgeting practices are crucial for planning and resource allocation and less important for performance evaluation. The results show that firms emphasize certain budget functions during the economic crisis [25].

According to Chenhall and Moers, MCSs must adopt innovations to cope with uncertainty [10]. They specifically argued that these systems should become more complex and include not only traditional tools (budget and variance analysis) but also new and innovative MA techniques such as ABC, SBSC, Target costing and Life Cycle costing. These innovations improve the decision-making process and contribute to the more effective use of management control. In addition, these innovations provide extensive information for carrying out internal controls and ultimately contribute to increasing an enterprise's profitability. Moreover, Zawawi & Hoque argue that recent global economic developments and uncertainty may affect the adoption of MAIs [9]. More analytical and more integrated information that companies provide to other companies can also reduce uncertainty [28].

Although management systems provide improvements in the efficiency and productivity of cost management, there is no significant change in management techniques as a result of the studies performed [29], [30]. This study reveals that accounting principles and standards used by organizations in the application of management systems have not changed. This is technically necessary to use all the functions of strategic cost management business

analysis techniques (eg, descriptive, predictive and normative data analysis, large data from both internal and external sources, and financial and non-financial information) to provide vital management information in the business environment.

Although valuable studies have been carried out in the social sciences and especially in the macroeconomic area in relation to early warning systems, there has not been a satisfactory study in the microeconomic area. Therefore, as a result of the recent economic crises, the failures of many businesses to maintain their activities have increased the interest on research area of crises. Numerous studies have been conducted using parametric and non-parametric tests to determine the timing and areas of policies to be developed against crises and to understand which indicators are effective on crises.

Frankel and Rose [31], Sachs *et al.* [32] are among of those who use these techniques. Non-parametric indicators or the second category known as signal approach has been popularized by Kaminsky *et al.* [33]. Brüggemann and Linne [34] and Edison [35] have taken the research further in this area, suggesting that many variables should be selected as the leading indicators of a crisis and reference values should be determined depending on these indicators to determine the signal of the crisis. They suggested that statistical tests could be used to investigate the non-sample performance of these indicators. Berg and Pattillo [36], Bussiere and Mulder [37] and Berg *et al.* [38] show that non-sample tests and other signal-based models are very successful in predicting financial crises.

Artificial neural networks have two important uses in economics such as classification of economic events and estimation of time series. Artificial neural networks focus on prediction of financial crises in a few applications and are widely used in bankruptcy forecasts. Nag and Mitra [39], for example, used a dynamic artificial neural network model to test the performance of artificial neural networks in predicting currency crises in Malaysia, Thailand and Indonesia, and to compare the results with the results of the signal approach. They show better results than KLR [33] model, especially when compared to non-sample estimates. Franck and Schmied [40], who conducted research on artificial neural networks, showed that a multilayer sensor performs better than the logit model in predicting money crises, and in particular in predicting money crises in Russia and Brazil in the 1990s [41]. Swanson and White also concluded that artificial neural networks improve the predictions of macroeconomic variables [42].

The use of micro data to determine whether businesses are sustainable in the long run does not provide sufficient information about the future of enterprises. In forecasting crises, it is very difficult for the business to predict only by looking at the internal data. Because crises are reflected to the financial statement of the enterprises after a long time. Therefore, in this study, as a result of the use of macro data in addition to micro data, it is tried to prevent possible losses

of companies by taking necessary precautions by predicting economic crises early.

This study is divided into the following sections: The next section presents a literature review. In the third section, SBSC based on Early Warning system is mentioned in detail. In the fourth part, an explanation of the theoretical knowledge and methodology related to the study is given. The last section discusses and concludes the findings of the study. It is widely accepted that innovation is a prerequisite for a business to succeed [13]. Innovation is the adoption of an idea or behavior that is linked to a product or service or a technical procedure, which is something new for the business adopted [43]. MAI is the first application in MA adopted by a business [9].

II. SUSTAINABLE BALANCED SCORECARD BASED ON EARLY WARNING SYSTEM

One of the most common strategic cost management tools used is the BSC developed by Kaplan and Norton [21]. BSC is used to link critical success factors with strategy and to observe success of an enterprise in achieving its strategic objectives. The BSC acts as an action plan that forms the basis for realizing the strategy expressed by critical success factors. Möller & Schaltegger introduced the concept of Sustainable BSC (SBSC) by integrating sustainability issues into the current perspectives of BSC (financial, customer, business business processes and learning and growth) [44]. In enterprises, SBSC provides a framework for the development of corporate responsibility and control of sustainability [45], [46].

In integrating sustainable management into the BSC, Zingales *et al.* proposed the creation of two separate environmental and social scorecards by dividing an enterprise's social and environmental responsibilities into two parts [47]. Bieker and Gminder [48] identify five different possibilities for structuring SBSC sustainability:

- Integrating one or two sustainability indicators into one of the classical perspectives (possibly internal process or customer perspectives),
- Adding a fifth perspective for environmental and social sustainability,
- Adding sustainability indicators to all four BSC perspectives,
- Sustainability, environmental and social perspectives that can be considered as the value factor of an organization, as the leading indicators in all perspectives,
- SBSC is created for only parts of the organization to promote the idea of sustainability,

The BSC has a flexible structure in terms of increasing perspectives or redefining critical success factors. Therefore, many studies have been carried out regarding the reconstruction of environmental, economic and social aspects, which are the cornerstones of sustainability. Figge *et al.* [49] in relation to these studies remarks that all relevant aspects help to consider in a balanced and simultaneous way to achieve sustainability. Because BSC has high potential to integrate environmental and social aspects into the overall management system, SBSC is integrated with parameters of sustainability

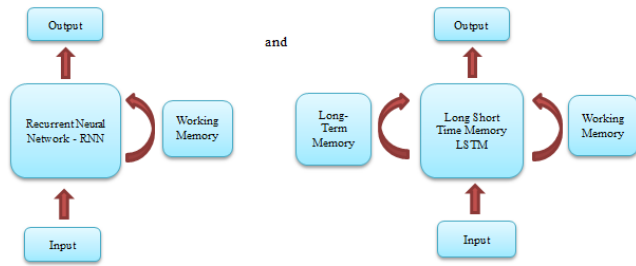


FIGURE 1. Relationship between RNN and LSTM.

to provide meaningful data to management. However, no serious studies have been conducted on the economy, which is one of the important parameters of sustainability. On the other hand, global economic crises are one of the most important problems related to the sustainability of enterprises. In this study, sustainability of companies is provided by integrating early warning systems for economic crises with the help of artificial neural networks and SBSC in order to eliminate the related problem.

III. THEORETICAL INFORMATION AND METHODOLOGY

A. LONG SHORT TIME MEMORY NETWORK

Although conventional recurrent neural networks (RNN) are capable of effectively modeling nonlinear time series problems, Gers et al. developed Long Short-Time Memory Network (LSTM) neural networks [50], [51]. Learning to process time sequences with conventional RNNs is based on predetermined time delays, so it is a difficult task to automatically find the optimal time window size.

RNNs have a very oblivious nature. This struggle with short-term memory causes RNNs to lose their effectiveness in most missions. LSTMs have an active memory. Although LSTMs are a kind of RNN, they function similarly to conventional RNNs, but are separated from RNNs by the gating mechanism. This feature addresses the “short-term memory” problem of RNNs. LSTM neural networks are initially introduced by Hochreiter and Schmidhuber, and the main objective of LSTM is to model long-term dependencies and to determine the optimal time delay for time series problems [52], [53].

As can be seen from Figure 1, the main difference between RNN and LSTM is the ability to maintain long-term memory. This feature is important for most of the natural language processing, time series and most of the sequential tasks. Figure 2 shows the traditional RNN architecture. In the normal RNN cell, the input in a time step and the hidden state in the previous time step are passed through a hyperbolic tangent (tanh) activation function to obtain a new hidden state and output.

On the other hand, LSTMs have a slightly more complex structure than RNN structures. At each time step, the LSTM cell receives 3 different pieces of information, namely the current input data, the short term memory of the previous cell (short term memory) and finally the long term memory.

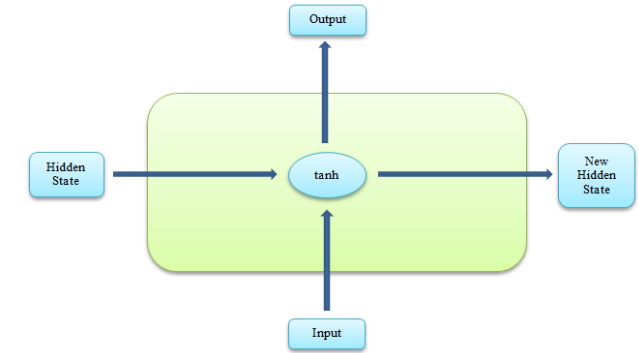


FIGURE 2. RNN internal working principle.

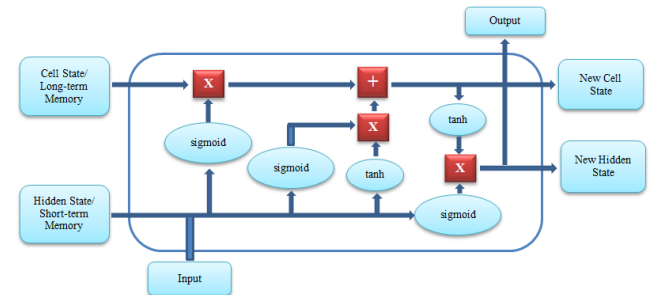


FIGURE 3. LSTM architecture.

Short-term memory is often referred to as a latent state, and long-term memory is often known as a cell state. The cell then uses the transition gates to organize the information to be stored or discarded at each step before forwarding the long and short term information to the next cell. Ideally, the role of these gates can be defined as the elimination of any irrelevant information.

The LSTM architecture consists of an input layer, a repetitive hidden layer, and an output layer. Unlike traditional neural networks, the basic unit of the hidden layer is the memory block [54]. The memory block includes self-connected memory cells that store the transient state and a pair of adaptive multiplicative switching units for controlling information within the block. Two additional gates, called the entrance gate and exit gate, respectively, control the input and output activations to the block. The core of the memory cell, a self-connected, linear Unit-Constant Error Carousel (CEC) and activation of the CEC represent the cell state. Because of the presence of the CEC, the crash doors can learn to open and close the doors, so that the LSTM can fix the lost error by keeping the network error constant. An oblivious gate is added to the memory block to prevent an unlimited growth of internal cell values when processing continuous non-split time series. This allows for self-resetting of the memory blocks when the accumulation ends, and then changes the CEC weight with multiplicative oblivious gate activation.

The entry door decides which new information is stored in the long-term memory. It only works with the information in the current input and the short-term memory in the previous

time step. It should therefore filter information from these variables that are not useful [55].

Mathematically, this process is carried out using two layers. The first layer is a filter that selects which information can pass through and which information to discard. To create this layer, it is necessary to transfer the short-term memory and the current input to a sigmoid function. The sigmoid function converts values between 0 and 1; 0 indicates that some of the information is insignificant, and 1 indicates that the information will be used. In this way, the values to be kept, used and also the values to be discarded are grasped. While the layer is trained by back propagation, the weights in the sigmoid function are updated to learn to provide only useful transitions while assigning less critical properties [56].

The input vector for the model is defined as $x = (x_1, x_2, \dots, x_T)$ and the output is $y = (y_1, y_2, \dots, y_T)$, where T is the estimated time. The purpose of the LSTM is to predict the economic crisis in the next step based on previous information without specifying how many steps needed to be taken back. To achieve this goal, the predicted crisis will be recursively calculated by following the Equations (2) - (7).

$$i_t = \sigma(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i) \quad (1)$$

$$f_t = \sigma(W_{fx}x_t + W_{fm}m_{t-1} + W_{fc}c_{t-1} + b_f) \quad (2)$$

$$c_t = f_t \otimes c_{t-1} + i_t \otimes g(W_{cx}x_t + W_{cm}m_{t-1} + b_c) \quad (3)$$

$$o_t = \sigma(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o) \quad (4)$$

$$m_t = o_t \otimes h(c_t) \quad (5)$$

$$y_t = W_{ym}m_t + b_y \quad (6)$$

\otimes symbol represents scaler multiplication of two vectors and $\sigma(\bullet)$ term specifies the standard logistic sigmoid function defined in Equation (2). This term can be calculated by Equation (7).

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (7)$$

The memory block is outlined in a closed box and consists of an input gate, an output gate, and a forgetting gate in which the outputs of the three gates are represented as i_t , o_t , f_t respectively. The activation vectors for each cell and memory block are shown as c_t and m_t , respectively. Weight matrices W , and bias vectors b are used to establish a connection between the input layer, the output layer, and the memory block.

$g(\bullet)$ is a central logistic sigmoid function within a range of $[-2, 2]$ given in Equation (8).

$$g(x) = \frac{4}{1 + e^{-x}} - 2 \quad (8)$$

$h(\bullet)$ is a central logistic sigmoid function within a range of $[-2, 2]$ given in Equation (9).

$$h(x) = \frac{2}{1 + e^{-x}} - 1 \quad (9)$$

The LSTM training is based on a modified version of RTRL-Time Recurrent Learning using the method of Back

TABLE 1. Input data and abbreviations.

Variables	Abbreviations
Banking Sector Loans	BSL
Consumer Price Index	CPI
Ratio of Exports to Imports	REI
Gross Reserves	GR
Current Foreign Currency Deposit Account	CFCDA
Borsa Istanbul Closing	BIC
Portfolio Investment	PI
Net errors and deficiencies	NED
Monthly Deposit Interest (TL)	MDI
CPI Based Real Exchange Rate Index	CPIBREPI
Interest for Dollar	ID
Automotive Production	AP
Domestic Debt Stock	DDS
Overnight Interest	OI

Propagation Through Time (BPTT) and Gradient Descent Optimization [57], [58]. The common goal is to minimize the sum of square errors. Errors are interrupted when they reach the output of a memory cell and then enter the linear CEC of the memory cell, where errors can be withdrawn forever and that the errors outside the cell tend to exponentially deteriorate [50]. This explains why LSTM is capable of handling arbitrary time delays in time series with long time dependencies [59].

B. MODEL DEVELOPMENT AND DATA SET

By using the monthly data of economic activities in Turkey in 1996 January - November 2009 period from the, the leading indicator of the crisis has been identified and tried to reveal using the LSTM neural networks.

Among the selected variables, Banking Sector Loans (BSL), Gross Reserves (GR), Demand FX Deposits, Portfolio Investment, Net Errors and omissions, Domestic Debt Stock are taken into account on a quantitative basis, Consumer Prices, Imports Coverage Rate, Monthly Deposit Interest, The Dollar Interest is expressed as a percentage. As the name implies, Borsa Istanbul Closing Index and CPI-Based Real Exchange Index are taken into consideration. Automotive production was evaluated on a unit basis.

The data in Table 1 are obtained from the websites of the Central Bank of Turkey, Turkish Statistical Institute and the Ministry of Finance. Data for Gross Reserves, Portfolio investments and Net Errors and deficiencies are in dollars. These data obtained in TL are exchanged with dollar using the average dollar exchange rate.

C. LSTM MODEL

When the data is analyzed, it is seen that there are differences between the economic data of the crisis periods and the data of the years of normal course. In order to obtain these

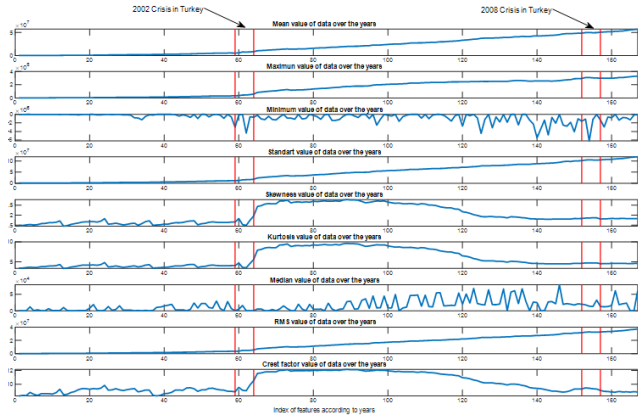


FIGURE 4. Distribution of economic data over the years (crisis is enclosed in red box).

differences, statistical feature in time space is extracted from economic data. These features are given below.

- RMS
- Kurtosis
- Standard deviation
- Skewness
- Maximum
- Minimum
- Average
- Median
- Crest factor

Table 2 shows examples of features obtained from the economic crises of Turkey in 2001 and 2008.

There are 14 economic data packages with 167 data in each, and 9×167 dimensioned feature matrix created with statistical properties in 9 time spaces. Feature matrix is given as an input matrix to LSTM model. The statistical data in Figure 4 are indexed and given graphically by months, starting from Jan, 2008. Features are indexed between 1 and 167. 59-64 index range represents the 2002 crisis period; 152-157 index range represents the 2008 crisis period, while other indices represent normal economic data. As seen in Figure 4, major changes have occurred during 2002 crisis period in Turkey on the data. The area between the red vertical lines indicates periods of crisis. When the graphs are examined, it is seen that skewness, kurtosis, crest factor are more dominant and deterministic than other features. Changes in these features are clearly seen during the crisis.

Once the inputs have been determined, the target output matrix is determined. The target output matrix of 1×167 was determined against the input matrix of 9×167 . The matrix has a value of 1 for the crisis period and 0 for the other normal periods. These values are hypothetical values and are given to indicate the crisis period.

Figure 5 shows the distribution of statistical features. It is seen that feature data effectively characterizes the determinants and periodic differences of distributions. After extracting the features shown in the statistical distribution, the LSTM neural network model is simulated with codes

TABLE 2. Values of some features in time space during sample crisis periods.

Features	Crisis of 2001	Crisis of 2008	Normal Period of 2005
Average	5940248,36071429	49359229,52857142	9837123,9921429
Maximum	36420620,00	304263121,00	235173000,00
Minimum	-148452,34	-1162918,4	-215908,65
Standard Deviation	12178689,093789	104580433,09720666	767398,5006689
Skewness	1,82732591029733	1,86487515968891	2,38649108547959
Kurtosis	4,67924573558507	4,725087007863187	6,0547328888551
Median	4818,08	12942,59	14889,145
RMS	3808419,44110603	32490490,5833169	20534193,3449627
Crest factor	9,56318508589035	9,36468226663933	11,4527508360922

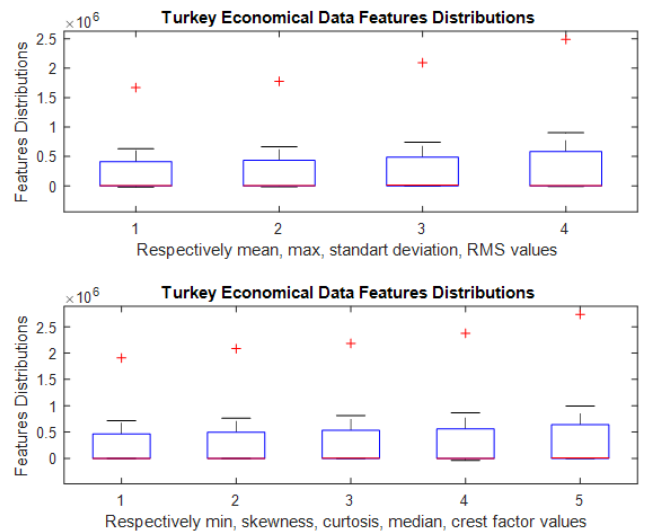


FIGURE 5. The statistical distribution of the data feature Turkey's economy.

written using the MATLAB Deep Learning Toolbox. Simulation parameters are determined by trial and error method. The 'man' optimization as the solver during the training phase is set so that the graded threshold value is 1 and the maximum epoch number is 100. The number of mini batches is chosen as 32 to reduce the amount of padding.

According to the network structure in Figure 6, a sequence of input layers is first calculated with the defining features and then the model starts with an LSTM layer. By subtracting

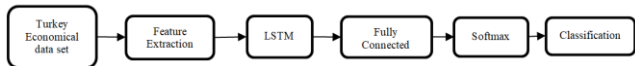


FIGURE 6. Classification stages of LSTM.

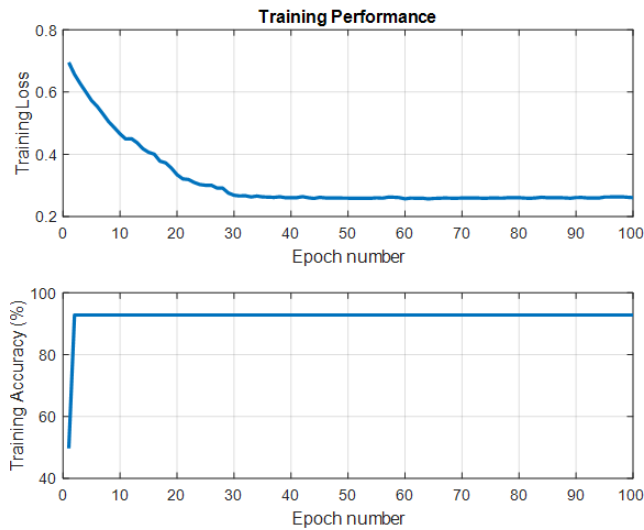


FIGURE 7. LSTM training performance.

the feature, more qualified data supporting LSTM model is given as input. To estimate the class labels, it terminates with a fully networked layer, a softmax layer, and a classification output layer. The input layer array size is selected to be the same as the number of properties of the input data. (Fully connected Layer) The size of the layer that is fully connected is determined by the number of classes to 2 (crisis or no crisis). The softmax layer generates the probability-based loss value using the score values generated by the fully connected artificial neural network. Softmax results in the probability value for the similarity of the test input for each class. The output values of the LSTM neural network model are non-normalized values. Softmax normalizes these values and converts them to probabilistic values. After obtaining the probabilistic values of the classes, the estimated classes obtained in the classification layer are determined according to their probabilistic values.

D. EXPERIMENTAL RESULTS

After the proposed feature matrix is given to the proposed model, the training phase is carried out with the model. Only the part of the data that does not belong to the importance of crisis is used during the training phase. Then, during the testing phase, the crisis period data will be used to verify the validity of the system. Figure 7 shows the performance graph of the LSTM training simulation. It is observed that the training loss value gradually decreased as desired and the accuracy of the training does not increase after a certain level. The training accuracy and test accuracy are close to each other since over fitting is prevented. The training phase is carried out successfully and the data is tested on the model developed.

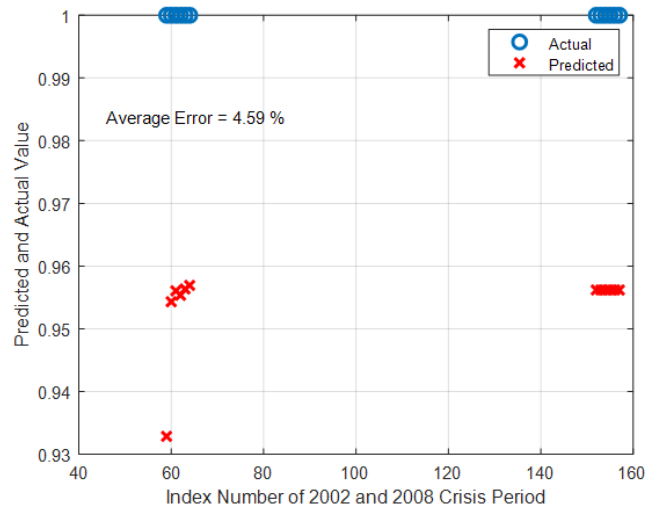


FIGURE 8. Actual and predicted output during crisis periods.

After the completing model training phase, the model is tested to verify the effectiveness of the proposed LSTM neural networks algorithm. Crisis data are used to test the model. The LSTM model output is given a value of 0 to represent the normal period and a value of 1 to represent the crisis period. Figure 8 shows the distribution of the estimated values according to the targeted values. Since the estimated values are determined as the crisis period, it is expected to be gathered around 1 (ie. around the crisis period data). As a result of the estimation, average error value is calculated and shown in Figure 8. The average error coefficient formula is found using Equation (10), here a_i and p_i represent real values and predicts the number of variables respectively.

$$Average\ Error\ (\%) = \frac{1}{N} \sum_{i=1}^N \left| 100 \frac{(a_i - p_i)}{a_i} \right| \quad (10)$$

The blue values in Figure 8 show the target output and the red values show the results predicted by the LSTM neural network model. The index data represent the 2002 crisis period in the 59-64 range and the 2008 crisis period in the 152-157 index range. When the graph is examined, it is seen that the classification of the error size has been achieved with a success rate of 95.41%. In other words, the crisis period data is estimated with a small margin of error of 4.59%. The values in the graph are for test data only. In other words, the data used during the LSTM training phase were not used during the test phase.

IV. CONCLUSION

In this study, a model has been developed to identify the most important macro variables affecting future economic crises and the performance of enterprises. The goal is to find the best model to predict the crisis beyond the historical data of the model. On the other hand, Enterprises may encounter unsuccessful results if they attempt to predict or manage the crisis with microdata. This is because the effects of economic crises on financial statements of the enterprises emerge at

least six months after the crises. Therefore, it is not possible to establish an early warning system with related micro variables. In this study, early warning system was established by considering macro variables besides micro variables.

However, the early warning system for crises is integrated with the SBSC. In this context, the problem of sustainable performance of enterprises in the period of economic crisis is an important criterion because of the important role of the country in environmental, social and economic terms. When businesses face crises, they face undesirable economical and financial consequences. In order to avoid these results, the SBSC approach should be added from another perspective that will show changes related to the external environment since it is important to evaluate business performance before and after the crisis in order to rapidly transform business processes into strategies. Therefore, a new model based on multiple criteria under environmental developments is presented.

The study reveals many important features. First, LSTM has expanded the scope of information about neural networks and their applications. Here, LSTM neural networks have been shown to be very successful in predicting economic crises in Turkey, when compared with traditional forecasting models, as a result of broadening the scope of application.

With this model, it has been shown that economic crises can be predicted and a system that will be followed with early warning system, which is a new dimension of SBSC, is designed. It is aimed to design a model that can make instant decisions by establishing a real-time model in the following stages. The results of this study are found to be very successful in predicting the crises of 2002 and 2008 in Turkey using LSTM neural networks with 95.41% accuracy.

With this model, in order to develop a strategy map as a reference for new developments in the future, a dynamic framework analysis of the organizations will be provided as well as the relevant indicators are monitored monthly through BSC and decision makers will be able to make healthy decisions and the enterprises will maintain their sustainability during crises with the least loss.

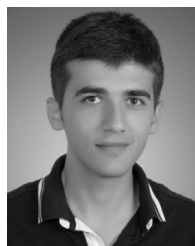
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