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Hybrid ConvLSTM Model for Evaluating the Performance of SMEs in The Software Sector

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ABSTRACT

SME is a term used for businesses based on the number of employees, size, and turnover. SMEs form the basis of the economy and are indispensable organizations of business life worldwide. In this study, the ConvLSTM model was created to evaluate the financial performance of SMEs operating in the software sector in Turkey. The motivation of the study is to analyze the performance of SMEs operating in the software sector in Turkey. The study used data from the Small and Medium Enterprises Development of Türkiye for 2018-2022. ConvLSTM was compared with LR, LSTM, SVM, CNN, RF, and MLP. Experiments showed that ConvLSTM outperformed other models, performing above 0.8 R^2 for all parameters.

Keywords: SMEs; CNN; Deep learning; LSTM; Machine learning; Software sector

1. Introduction

The concept of SME, an abbreviation for Small and Medium-sized Enterprises, is a crucial classification of businesses across sectors. It takes into account factors such as annual net sales, annual financial balance sheet, and number of employees [1]. SMEs are further categorized into small-sized enterprises, micro-sized enterprises, and medium-sized enterprises [2]. These categories are determined based on the company's financial situation and the number of employees [2]. However, it's important to note that the turnover and number of employees limits of these transactions vary from country to country, reflecting the unique economic conditions of each nation [3, 4].

The software industry is essential to daily life and the economy [5]. Software is one of the essential tools that enable many essential tools for commercial and social life to be carried out effectively, efficiently, and collaboratively [6]. Communication and information technologies have become an essential part of social and commercial life and public services, and integrating these technologies with people and other technologies puts the software sector in a critical position [7]. The software industry generally includes creating a product compatible with hardware through analysis, developing programming, performing tests, marketing and distributing the product, and performing after-sales maintenance [8].

The software industry is a sector with low investment costs but high added value, making it a key driver of economic development. Its influence extends to both the industry and the service sector, making it a crucial element in the transition to the information society [9]. The software production process relies heavily on knowledge, intelligence, and creativity, making it a vital factor in boosting the development of countries, reducing unemployment, and enhancing national and international competitiveness [10].

In this study, the current ratio, operating profit before depreciation, revenues, expenses, number of working capital days, profit-loss, liquidity ratio, cash ratio, net working capital, net sales revenue, profitability of equity, return on sales of companies operating in the software sector in Turkey are examined. The motivation of this study is to develop a forecasting model to analyze the financial performance of companies operating in the software industry in Turkey. It was aimed to predict 13 parameters, such as profitability and cost of sales over the years. Data from 2018-2022 provided by the Small and Medium Enterprises Development Organization of Turkey was used. For this purpose, the ConvLSTM model was developed by hybridizing CNN and LSTM models. The effectiveness of the ConvLSTM was compared with RF, LR, SVM, LSTM, MLP, and CNN.

The innovations of this study are as follows:

- A hybrid prediction model was developed to benefit from the effective features of LSTM and CNN

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models.

- There is no previous study in the literature on the software industry.
- It was aimed to create the productivity ranking for the years 2018-2022 by using the TOPSIS method.
- Data augmentation was performed on SMEs data using the Synthetic Minority Over-Sampling Technique for Time Series (SMOTE-TS).
- ConvLSTM was compared in detail with traditional models.

2. Related Works

This section examines studies in the literature where artificial intelligence methods were applied to SMEs to understand their economic contributions and determine trends among businesses.

Zhu et al. [11] developed a hybrid model for estimating the credit risks of SMEs. In the study, the model developed using MultiBoosting and Random Subspace methods was compared with base models and a decision tree. Approximately two years of data from 46 SMEs were used as the dataset. Experiments have shown that the developed model is more effective than the base models.

Belhadi et al. presented an ensemble learning model to estimate credit risk associated with agricultural SME investments [12]. The developed model had 91.3% accuracy, 87.6% sensitivity, and 89.2% recall value in predicting credit risk.

Malakauskas and Lakstutiene [13] presented a comparative analysis of machine learning algorithms for the financial distress prediction of SMEs. The dataset used in the study relates to 12,000 SMEs. Logistic Regression (LR), RF, and Artificial Neural Networks (ANN) were compared in the study. Experiments showed that RF outperformed other methods with 0.68 AUC.

Schalck and Yankol-Schalck [14] presented a machine learning-based comparative analysis of business failure prediction using approximately 7 years of French SME data. In the study, LR, Probit, and XGBoost algorithms were used. Experiments have shown that XGBoost outperforms compared models.

Kou et al. compared machine learning methods for bankruptcy prediction, which is critical for SMEs, using two-stage and multi-objective feature selection [15]. The model proposed in the study had a prediction accuracy of 92.5%. The multi-objective feature selection method reduced the feature set by 78%.

Hamal and Şenvar [16] aimed to detect financial accounting fraud using approximately 5 years of data from 341 Turkish SMEs. In the study, a dataset consisting of fake and normal loans received from banks was used. Experiments using Bagging, SVM, ANN, Naive Bayes (NB), k-Nearest Neighbor (kNN), RF, and LR showed that RF was more successful than other compared models with 0.9374 accuracy, 87.2% precision, and 91.5% recall.

3. Material and Method

In this study, an analysis was carried out using 2018-2022 data to evaluate the financial performance of SMEs operating in the software industry in Turkey. In this analysis, the effectiveness of a hybrid model developed by taking advantage of the features of CNN and LSTM models was compared with traditional models such as RF, LR, SVM, LSTM, MLP, and CNN. In this section of the article, detailed explanations of the dataset and the developed model will be presented.

3.1. Dataset

The software industry is divided into 12 regions by the Turkish Statistical Institute (TURKSTAT), as seen in Table 1.

Table 1. Regions where the software sector is divided by TURKSTAT

Region name	Provinces covered by their regions
İstanbul	İstanbul
Western Marmara	Tekirdağ, Kırklareli, Edirne, Çanakkale, Balıkesir
Aegean	Denizli, Uşak, Aydın, Muğla, Afyonkarahisar, Manisa, İzmir, Kütahya
Eastern Marmara	Bursa, Bolu, Bilecik, Sakarya, Kocaeli, Eskişehir, Düzce, Yalova
West Anatolia	Konya, Ankara, Karaman
Mediterrenian	Hatay, Antalya, Adana, Kahramanmaraş, Osmaniye, Isparta, Mersin, Burdur
Central Anatolia	Kırıkkale, Niğde, Kırşehir, Sivas, Kayseri, Yozgat, Aksaray, Nevşehir,
West Blacksea	Zonguldak, Bartın, Çankırı, Sinop, Tokat, Çorum, Karabük, Kastamonu, Amasya, Samsun
East Blacksea	Trabzon, Rize, Giresun, Gümüşhane, Ordu, Artvin
Northeastern Anatolia	Erzurum, Kars, Bayburt, Iğdır, Ağrı, Erzincan, Ardahan
Middle East Anatolia	Bitlis, Malatya, Hakkâri, Elazığ, Muş, Tunceli, Bingöl, Van
Southeastern Anatolia	Gaziantep, Kilis, Diyarbakır, Şanlıurfa, Şırnak, Adıyaman, Siirt, Batman, Mardin

Statistical analyses are made according to these regions. This study conducted a comparative productivity analysis with the Turkey average and Level 1 average of the software industry using financial data between 2018-2022. This analysis aims to create a productivity ranking for the years 2018-2022 by using the Technique for Order Preference by Similarity (TOPSIS) method, one of the multi-measure decision-making methods, based on both the financial data of the software industry and the averages of both Turkey and 12 regions. Additionally, changes in the performance of the software industry were examined by comparing the productivity rankings of 12 regions in the last five years with Turkey's general productivity rankings. Normalized and weighted decision matrices were created by combining the initial matrices of 12 regions.

TOPSIS is a multi-criteria decision-making method [17]. TOPSIS evaluates decision options based on positive and negative ideal solutions. TOPSIS is used in decision-making processes with many criteria [18]. The first step in the TOPSIS method is to create the decision matrix. At this stage, criteria are determined [19]. The matrix rows show the options, and the columns show the business criteria. The decision matrix is seen in Eq. 1.

$$D_{ij}=\begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ d_{ij} & d_{i2} & \cdots & d_{in} \\ \cdots & \cdots & \cdots & \cdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \quad (1)$$

After the decision matrix is created, the standard decision matrix is obtained by using Eq. 2 and 3.

$$\forall\ d_{ij} \neq 0:\ r_{ij} = d_{ij}r_{ij}\ \frac{d_{ij}}{\sqrt{\sum_{k=1}^{m} d_{kj}^2}}\ \forall_i = 1,\ldots\ldots,m \quad \forall_i = 1,\ldots\ldots,n \quad (2)$$

$$\forall d_{ij} = 0: r_{ij} = 0;\ \ \forall_j = 1,\ldots\ldots.m,\ \ \forall_j = 1,\ldots\ldots n \quad (3)$$

Eq. 2 is used for the normalized decision matrix. As a result of the normalization process, the decision matrix is formed as in Eq. 4.

$$R_{ij}=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{ij} & r_{i2} & \cdots & r_{in} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \quad (4)$$

In creating the weighted standard decision matrix, the weights of the criteria w_j are obtained as in Eq. 5. Total must be 1.

$$V_{ij}=\begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots\ w_n r_{1n} \\ w_2 r_{21} & w_2 r_{22} & \cdots\ w_n r_{2n} \\ \vdots & \vdots & \cdots \\ w_1 r_{m1} & w_2\, r_{m2} & \cdots\ w_n r_{mn} \end{bmatrix} \quad (5)$$

Negative ideal and positive ideal solutions are made using Eq. 6 and 7.

$$\boldsymbol{A^* = \{\left(\max_{i} v_{ij} \setminus j \in j\right), (\min_{i} v_{ij}\ Jay \in j')}$$

$$A^* = \{\ v_1^*, v_2^*, \ldots\ldots.\ v_j^*, \ldots\ldots.\ v_n^*\ \} \quad (6)$$

$$A^- = \{(\left(\min_{i} v_{ij}\ Jay \in j'\right),\ \left(\max_{i} v_{ij} \setminus j \in j'\right)\ \ i = 1,\ldots.,m \quad (7)$$

$$A^- = \{\ v_1^-, v_2^-, \ldots\ldots.\ v_j^-, \ldots\ldots.\ v_n^-\ \}$$

Eq. 8 and 9 are used to calculate the separation measures.

$$S_j^* = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^*\right)^2} \quad \forall_i = 1,\ldots.\,m \quad (8)$$

$$S_j^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}\ \ \forall_i = 1,\ldots\ldots,m \quad (9)$$

Eq. 10 is used to calculate the relative closeness to the ideal solution.

$$C_i^*\ \frac{S_i^-}{S_i^- + S_i^*} \quad 0 \le C_i^* \le \forall_i\ = 1,\ldots.\,m \quad (10)$$

$C_i^*, 0 \le C_i^* \le 1$ takes values in the range.

Table 2 shows the initial matrix of the 2nd region as an example.

Table 2. The initial matrix

Variable	2018	2019	2020	2021	2022
Current ratio	2	2.33	1.94	2.04	1.97
Operating profit before depreciation	16.41	8.12	24.17	28.16	31.94
Revenues	34359.3	39900.94	66125.93	69499.57	109341.24
Expenses	27580.49	36949.05	33680.75	36696.28	69870.55
Number of working capital days	53.11	41.18	58.59	48.04	60.14
Profit-loss	2110.11	3227.11	6919.63	10425.45	14203.98
Liquidity ratio	1.28	1.35	1.36	1.3	1.06
Cash ratio	0.43	0.46	0.65	0.57	0.55
Net working capital	23344.05	32736.22	78165.35	40891.38	58205.45
Net sales revenue	32935	34232.27	57388.03	63866.93	101720.33
Profitability of equity	0.24	0.27	0.31	0.37	0.38
Profitability of sales	0.1	0.13	0.19	0.22	0.24
Cost of sales	2335.98	4081.11	2513.4	897.7	2169.69

The dataset was structured with data augmentation using SMOTE-TS to have a data abstract of 10000 rows. SMOTE-TS is a method that aims to improve the class balance of classes with a small number of samples in time series data [20]. SMOTE-TS aims to generate synthetic samples while preserving temporal relationships. SMOTE-TS preserves relationships between samples with the help of a time window. The time window selects samples from the minority class based on the similarity measure and creates synthetic samples by interpolating over time.

Augmented data was scaled using MinMaxScaler. 80% of the dataset was used for train and 20% for test. 10% of the training data was used for validation to select the hyper-parameters of the models. Model hyper-parameters were determined using GridSearch. GridSearch aims to determine the most successful hyper-parameter combination by trying specified hyper-parameter combinations [21].

3.2. Baseline Models

LR uses a linear equation to model the relationship between two or more variables. LR attempts to draw a line graph between the independent variable x and the dependent variable y [22]. The goal of LR is to find a line that best represents the relationship between variables x and y. This line should be as close to the data points as possible [23].

RF is based on selecting the prediction results of multiple decision trees using the voting method [24]. Unlike traditional decision trees, RF performs the steps of finding the root node and dividing the nodes randomly. When expanding RF trees, it looks for the best features among random subsets of features. In this way, it is possible to create a model with a wider variety of RF [25].

SVM is based on determining a hyperplane to separate the points on a plane [26]. Hyperplanes represent the points in space, and the support vector refers to the samples obtained by passing through these points [27]. Margin refers to the distance between the hyperplane and the samples. It focuses on capturing instances by drawing another hyperplane with the largest possible margin between the hyperplane and the support vector. It maximizes this margin to obtain the best decision limit [28].

MLP is a feed-forward neural network inspired by the information processing structure of the human brain [29]. The input layer provides input data. Hidden layers enable calculations and the learning process to take place [30]. The output layer is the layer where the outputs of the calculations made on the network are presented. The nodes in the layers with MLP are fully connected to the nodes in the previous layer. MLP allows updates to be made by propagating the error across the network using backpropagation [31].

CNN is a model that is generally used in image classification problems and is successful in feature extraction [32]. CNN can also be used in regression problems with the help of non-linear activation functions of the nodes in the output layer. Thanks to its convolution and pooling layers, CNN enables feature extraction and creation of high-level representations of the extracted features [33]. Features processed in fully connected layers are presented in the output layer.

LSTM is a deep learning model that contains feedback connections that can handle temporal dependencies in data [34]. LSTM memory cells enable data to be kept in long arrays by regulating the flow of information in memory cells. Thanks to the forgetting gate, LSTM determines which information in the memory will be forgotten or remembered [35]. LSTM copes with the vanishing gradient problem experienced in recurrent neural networks thanks to its gate units [36].

3.3. Hybrid ConvLSTM Model

ConvLSTM is a model that effectively analyzes time series data and has high prediction accuracy. While CNN is effective in extracting patterns in the data, LSTM is effective in learning time-dependent long—and short-term relationships, sequential dependencies, and dynamics. Figure 1 shows the architecture of the developed ConvLSTM model.

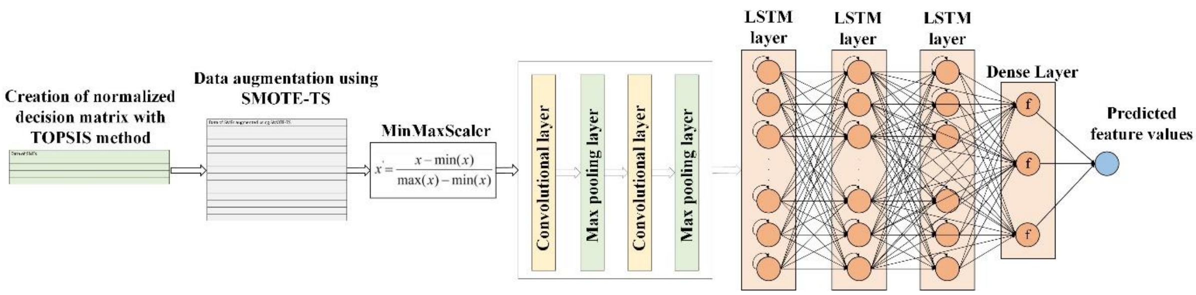

Figure 1. The architecture of the developed ConvLSTM model

The developed model benefits from the successful features of CNN and LSTM models. CNN effectively extracts features from data using convolution layers. LSTM, on the other hand, is effective for identifying long-term dependencies and time-dependent patterns in data. LSTM has gate units for forgetting past data and learning new data. ConvLSTM enables the extraction of spatial features with its CNN component. The LSTM component allows ConvLSTM to extract long-term dependencies and patterns in time series data. ConvLSTM successfully models complex data relationships by effectively learning spatial and temporal features. The hyper-parameters of ConvLSTM determined using GridSearch are filters=64, kernel_size=1, and activation= ReLU for Dual-layer Conv1D CNN. In the MaxPooling1D layer, the pool size is 2. 32 neurons were used in 3-layer LSTM. Adam was the optimizer, and ReLU was the activation function. The epoch number is 100, and the batch size is 32.

4. The Experimental Results

In this study, we aimed to predict 13 parameters, such as the profitability and cost of sales of companies operating in the software sector in Turkey over the years.

Parameters of the companies such as current ratio, operating profit before depreciation, revenues, expenses, number of working capital days, profit-loss, liquidity ratio, cash ratio, net working capital, net sales revenue, profitability of equity, profitability of sales, and cost of sales were used. Data between 2018 and 2022 provided by the Small and Medium Enterprises Development of Türkiye was used as the dataset. For this purpose, a ConvLSTM hybrid model was developed using CNN and LSTM. The prediction accuracy of the developed model was compared with RF, LR, SVM, LSTM, MLP, and CNN.

In this section, the experimental results of the compared models according to RMSE, MAE and R^2 metrics for the prediction of each parameter are presented. Table 3 shows the experimental results according to the RMSE.

Table 3. The experimental results according to the RMSE

Parameters	LR	RF	SVM	MLP	CNN	LSTM	ConvLSTM
Current ratio	0.041	0.039	0.031	0.019	0.028	0.016	**0.009**
Operating profit before depreciation	9.656	8.712	7.892	5.762	7.672	5.045	**3.166**
Revenues	1629.672	1589.267	1504.017	1412.522	1517.450	1318.231	**1208.512**
Expenses	982.641	971.646	952.454	896.784	917.870	831.534	**738.761**
Number of working capital days	12.943	12.244	10.287	7.959	9.692	6.922	**5.606**
Profit-loss	703.454	645.551	643.546	632.625	635.512	621.834	**607.751**
Liquidity ratio	0.235	0.199	0.192	0.181	0.187	0.174	**0.170**
Cash ratio	0.071	0.070	0.068	0.061	0.063	0.055	**0.035**
Net working capital	655.581	612.106	590.627	513.247	581.379	465.896	**402.137**
Net sales revenue	3707.614	2943.367	2879.590	2740.979	2803.261	2117.504	**1949.528**
Profitability of equity	0.045	0.043	0.036	0.030	0.034	0.021	**0.014**
Profitability of sales	0.097	0.081	0.072	0.056	0.059	0.044	**0.032**
Cost of sales	61.891	52.470	49.162	32.991	37.363	20.884	**18.306**

As seen in Table 3, ConvLSTM had lower RMSE than the compared models. After ConvLSTM, LSTM, MLP, CNN, SVM, RF and LR are successful, respectively.

Table 4 shows the experimental results according to the MAE.

Table 4. The experimental results according to the MAE

Parameters	LR	RF	SVM	MLP	CNN	LSTM	ConvLSTM
Current ratio	0.039	0.036	0.027	0.017	0.025	0.014	**0.008**
Operating profit before depreciation	8.971	8.044	7.257	5.221	7.135	4.911	**3.055**
Revenues	1579.515	1523.211	1477.442	1365.445	1474.211	1267.744	**1097.615**
Expenses	919.484	887.233	866.410	807.968	829.768	756.786	**702.646**
Number of working capital days	11.118	10.461	9.668	7.112	9.417	6.354	**5.145**
Profit-loss	12.396	11.950	10.416	8.442	9.220	7.737	**5.129**
Liquidity ratio	0.229	0.214	0.203	0.179	0.188	0.168	**0.161**
Cash ratio	0.068	0.065	0.060	0.057	0.055	0.051	**0.034**
Net working capital	663.802	597.305	546.039	488.406	494.577	453.498	**398.053**
Net sales revenue	3661.565	2884.996	2690.220	2242.406	2660.561	2109.749	**1701.764**
Profitability of equity	0.042	0.038	0.034	0.027	0.031	0.024	**0.013**
Profitability of sales	0.056	0.048	0.039	0.031	0.035	0.023	**0.019**
Cost of sales	44.225	50.455	39.921	32.477	37.205	19.651	**17.484**

As seen in Table 4, ConvLSTM had lower MAE than the compared models. After ConvLSTM, LSTM, MLP, CNN, SVM, RF and LR are successful, respectively. Table 5 shows the experimental results according to the R^2.

Table 5. The experimental results according to the R^2

Parameters	LR	RF	SVM	MLP	CNN	LSTM	ConvLSTM
Current ratio	0.502	0.544	0.670	0.774	0.691	0.816	**0.844**
Operating profit before depreciation	0.486	0.540	0.588	0.712	0.624	0.736	**0.803**
Revenues	0.517	0.553	0.635	0.697	0.647	0.751	**0.814**
Expenses	0.451	0.487	0.511	0.623	0.583	0.776	**0.853**
Number of working capital days	0.389	0.428	0.495	0.636	0.512	0.734	**0.848**
Profit-loss	0.512	0.627	0.712	0.762	0.738	0.791	**0.837**
Liquidity ratio	0.496	0.500	0.536	0.714	0.595	0.787	**0.865**
Cash ratio	0.445	0.591	0.672	0.864	0.709	0.903	**0.924**
Net working capital	0.340	0.503					
Net sales revenue	0.554	0.620	0.721	0.850	0.784	0.911	**0.937**
Profitability of equity	0.314	0.561	0.625	0.716	0.647	0.797	**0.879**
Profitability of sales	0.360	0.480	0.597	0.764	0.612	0.793	**0.823**
Cost of sales	0.522	0.545	0.656	0.866	0.791	0.921	**0.955**

As seen in Table 5, ConvLSTM had a higher R^2 than the compared models. After ConvLSTM, LSTM, MLP, CNN, SVM, RF and LR are successful, respectively.

According to the performance evaluation metrics in Table 3, Table 4, and Table 5, ConvLSTM is more successful than the compared models. ConvLSTM is more successful than LSTM and CNN because ConvLSTM combines the capacity of LSTM to process patterns over time and the capacity of CNN to learn spatial features. ConvLSTM can thus effectively model complex relationships and spatial features over time. ConvLSTM is more successful than MLP because MLP's structure, which consists of fully connected layers, is limited in processing sequential time series data. ConvLSTM is more successful than SVM because SVM is a feature-based model that cannot detect time-dependent patterns in time series data. LR and RF need to be improved to learn complex time series relationships. ConvLSTM can effectively learn complex time series relationships and long-term dependencies.

5. Conclusions

In this study, a hybrid ConvLSTM model was developed to evaluate the financial performance of SMEs operating in the software sector in Turkey. SME data operating in the software industry for 2018-2022, provided by the Small and Medium Enterprises Development Organization of Turkey, was used as the dataset. The dataset used includes 13 different parameters of SMEs, such as current ratio, operating profit before depreciation, revenues, expenses, number of working capital days, profit-loss, liquidity ratio, cash ratio, net working capital, net sales revenue, profitability of equity, profitability of sales and cost of sales.

The developed ConvLSTM model was created to increase prediction accuracy by combining the effective features of CNN and LSTM. ConvLSTM successfully modeled the complexity in the data by effectively learning spatial features thanks to the CNN component and temporal features thanks to the LSTM component. Experiments show that ConvLSTM is more successful than traditional models in evaluating the financial performance of SMEs in the software sector in Turkey and can be used effectively in creating productivity rankings.

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