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Research Article

Hybrid Deep Learning Model for Predicting the Contribution of SMEs to the Economy: A Case Study for Turkey

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Abstract

In this study, a combination of deep learning models was developed to calculate the economic contribution of SMEs. The hybrid model's advantage lies in its ability to leverage the strengths of CNN to identify spatial relationships and draw patterns, as well as LSTM to capture sequential temporal dependencies. The goal of this hybrid model was to provide an accurate estimate of the economic contribution of SMEs. To compare the effectiveness of the hybrid model, extensive comparative experiments were conducted using a dataset of economic indicators of SMEs in Tadrakea. The experiments demonstrated that CNN-LSTM outperforms other commonly used machine learning and deep learning networks. A hybrid model, combining CNN and LSTM, can be used to capture complex data, thereby improving prediction accuracy.

1. Introduction

Small and medium-sized enterprise (SME) is a very important role to provide business growth in economy, to provide employment, and in offering of new product, service, and business [1]. Small to medium size is one of the things that distinguish SMEs with big firms. SMEs are also responsive and more dynamic hence changes in the market place are handled in a short time [2]. The SMEs are represented in many spheres of the economy, and their interaction and involvement are obtained at different levels. To start with, SMEs can be viewed in a more comprehensive light and this also must be elementally put into consideration whenever looking at the outcomes of economic policies [3]. Economies rely on SMEs. SMEs provide employment opportunities and

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promote innovation development, as well as contribute to regional development [4].

To start with, SMEs are nimble and flexible; the innovation of new ideas, goods, and services finds its backing in alternative forms of markets. Just because a firm is small does not diminish the significance of the general contributions of SMEs to economic growth, international trade, and technology [5]. It is time to recognize SMEs, as they may wish to contribute to improved awareness of the economy and its policies, which will promote their success [6].

In Turkey, SMEs constitute 99.8% of all enterprises, provide approximately 72% of total employment, and account for nearly 50% of the country's GDP. According to the Ministry of Industry and Technology, SMEs also represent 56% of total exports, making them a critical driver of international trade performance. For example, in the manufacturing sector alone, SMEs have been responsible for more than 60% of sectoral employment and have played a pivotal role in regional economic development, particularly in Anatolian provinces where large-scale enterprises are scarce. These figures highlight the indispensable contribution of SMEs to Turkey's economic stability, innovation capacity, and sustainable growth.

SMEs play a crucial role in an economy, as they are major contributors to economic growth, innovation, and employment [7].

Therefore, the total impact of SMEs on the economy is crucial in terms of economic management, public policy, and resource allocation. Next, the phenomenon of deep learning, which has become an integral part of current artificial intelligence technology, presents some benefits in calculating the extent of SMEs' role in the economy [8]. Among the beneficial features of deep learning in determining the role of SMEs in the economy, one can single out the identification of complexity, utilization of big data, feature learning, flexibility, generalization, predictability, and accuracy [9].

Definition of Complexity: The inputs of SMEs to a given economy depend on the interaction of several factors. The perennial approaches to the study come at difficulty whenever there is an attempt to investigate the interrelationship of the variables. Such complexities in the information could be identified through deep learning, and consequently lead to more accurate results in terms of predictions [10].

Use Big Data: Big Data can be used, by accumulating information about SMEs in the past to use the insight in the future. The deep learning technique can analyze requisite data at great speed. This will make it possible to forecast the economic presence of SMEs in detail and in a comprehensive manner [11].

Learning of Features: The variety of aspects that can change the economic contribution of SMEs may be complicated and even complex to forecast by human being, because the features connected with value in the information can be identified by deep learning automatically [12].

Flexibility and Generalizability: The learning process allows models of deep learning to be highly flexible, capable of adjusting to new datasets and economic changes within a short time [13]. This particularly needs to be taken into account when contemplating the extent to which the economic input of the SMEs changes after the passage of time as well as current geographical locations.

Prediction Accuracy: Deep learning algorithms are also known to have greater accuracies in their prediction accuracy for dimensions that are large. In case of SMEs, economic impact of SMEs is of special significance in allowing prediction of their potential and hence planning and policy administration [14].

In conclusion, the projection of the economic value of SMEs can be educative, general, and precise through deep learning. This way, deep learning can be an informative input to the whole financial management and outlay based policy making process.

In this paper, CNN-LSTM has formulated Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNNs) as a technique to determine the contribution of SMEs to the economy. The use of the CNN-LSTM hybrid model has a number of advantages in making time series predictions. CNN can be applied to both long-run and short-run correlations in the time series data. CNN will derive the important features of time series data by detecting structures, forms, or patterns over a longer perspective. In this way, it identifies complex relationships throughout the entire dataset, as mentioned in [15]. CNN identified a difference in a moving pattern, making those motion observations similar to what is seen in image processing. Time series data can show how a motion or change of select patterns can also be used as a predictor of trends and turning points, often found in fluctuating data [16]. LSTM is a Recurrent Neural Network type which is able to capture long-term dependencies [17]. It is capable of providing an outlook on the future and preserve the effect of past temporal steps. Since CNN-LSTM hybrid model can be used on different industries and domains, as with the time series prediction in image processing [18] it is more versatile in the solving of different problems that concerns time series prediction. CNN can transform the input data into features of a lower level. Here, the complexity of tasks is transformed into simple features, rather than carrying out complex tasks on the available input data. Conclusively, the CNN-LSTM Hybrid Model can enhance the review of most time series data. Its ability to resist fluctuations and identify long-term dependencies, thereby eliminating any structural patterns, helped it yield better outcomes in different time series predictions. The research has contributed the following to the literature:

• The artificial oversampling technique of time series (SMOTE-TS) was used to augment the data. • The obtained hybrid model of this study was compared to linear regression (LR), support vector regression (SVR), a CNN, multi-layer perceptron (MLP), random forest (RF), and LSTM.

• The experimental findings revealed that the CNN-LSTM experiment is better successful than the compared models and it has a positive predictive performance used to forecast the respective contribution of SMEs to the economy.

2. Related Works

Many researchers have used predictive modeling to determine the economic contributions of SMEs. The researchers aimed to employ deep learning techniques to assess the economic contributions of SMEs. In this section, a detailed examination of the available literature on SME contributions to the economy using deep learning-based models is provided. Evaluating the process of designing strategies and examining different approaches can increase awareness of how this research can be further developed and prepare the ground for establishing the innovation model presented in this paper.

Afolabi et al. propose a new model based on machine learning algorithms to predict business performance [19]. In this research, an operational framework is established to accommodate various indicators that impact the business's performance. To confirm the predictive capacities of the model, a scientific study is conducted. The overall accuracy in predicting business success was 86%. The other measured predictive abilities were precision 89 percent and recall 82 percent. The numerical values of the variable sets presented demonstrate the effectiveness of applying machine learning algorithms in developing forecasts related to business success. The numerical values of the variable sets presented demonstrate the effectiveness of applying machine learning algorithms in developing forecasts related to business success. Unlike Afolabi et al., our study applies a deep learning-based hybrid CNN–LSTM architecture to time series SME economic data, aiming to capture both spatial and temporal patterns for improved prediction accuracy.

Belhadi et al. introduce a new machine learning-based ensemble approach to determine the credit risk associated with investments in Agricultural SMEs within the context of Agriculture 4.0, utilizing the supply chain finance framework [20]. This work aims to evaluate credit risk more effectively. They tried out several different machine learning algorithms on a huge dataset, and they found very substantial outcomes. Using the ensemble model, credit risk can be accurately ascertained with an accuracy rate of 91.3%, demonstrating that this model can effectively assess the level of risk exposure in terms of the potential risk associated with an investment. The precision score of the ensemble model was 87.6%, and the recall score was 89.2%. The above numerical results demonstrate the effectiveness of the technique introduced in this study and reveal it as a valuable tool that can help stakeholders of Agricultural 4.0 investment make informed credit decisions and assess the risks associated with such investments. This demonstrates that the model can effectively assess the level of risk exposure in terms of the potential risk associated with an investment. Our approach differs by focusing on macroeconomic performance prediction of SMEs in Turkey rather than credit risk, and by employing a hybrid deep learning model instead of ensemble tree-based methods.

Kou and co-authors scrutinize one of the most pressing problems nowadays: how to predict the bankruptcy of SMEs based on transactional data, using a two-stage multi-objective strategy of feature selection [21]. The authors tested the model by utilizing 15 alternative machine learning methods with very encouraging results. The prediction accuracy provided by the proposed model is 92.5%, which is rather incredible, especially considering the prediction of bankruptcies. The model not only performs sufficiently well on the task of prediction, but the multi-objective feature selection approach also reduces the feature size to a dramatically smaller one, resulting in a final feature set size that reports a 78 percent decrease. The numerical solutions reveal that the integrated model provides SMEs with a helpful way of tracking how at risk a company is to bankruptcy and thus how best to focus their strategic resolution. As a result, a final feature set size reporting a 78% reduction was obtained. In contrast, our work aims to estimate the economic contribution of SMEs and integrates CNN and LSTM to extract hierarchical features without feature selection as a preprocessing requirement.

Hamal et al. researched and compared various methods for detecting financial accounting fraud in SMEs [22]. The paper aims to provide feedback on the applicability of various classifiers in detecting fraud. The authors introduced a variety of machine learning algorithms and tested them extensively, with promising conclusions. The authors concluded that the Random Forest classifier performed the best, with an accuracy of at least 89.7%, and successfully detected fraudulent financial accounting cases. It had precision (87.2%) and recall (91.5%) values that supported its accuracy. It is not only an important number (data) in the area of accounting fraud, but it also demonstrates that random forest is applicable in detecting accounting fraud in Turkish SMEs, with potential benefits for those interested in fraud detection and risk management. While Hamal and colleagues focus on detecting accounting fraud in SMEs using classification algorithms such as Random Forest, we address a different dimension: estimating the macroeconomic contributions of SMEs and using a hybrid CNN-LSTM model that can capture both temporal and spatial dependencies in time-series economic data. Wang et al. strive to predict the credit risk of SMEs using a machine learning-based sampling strategy [23]. The objective of their research is to enhance the accuracy of historical risk assessments through advanced approaches and utilize these assessments to inform funding decision-making processes. They employ an extensive experimental process that incorporates machine-learning algorithms and sampling strategies. The results demonstrate that the sampling strategy effectively improves the prediction of SMEs' credit risk, exemplifying the utility of employing machine learning techniques in supply chain finance contexts. In general, the evidence relating to the research topic is encouraging as these techniques can be practically used to enhance the risk management of SMEs in supply chain networks when it comes to the lending process. Unlike Wang et al., who enhance SME credit risk prediction through sampling strategies, our research focuses on forecasting broader economic performance indicators of SMEs in Turkey, using deep learning architectures optimized via GridSearchCV to maximize predictive accuracy. Zhang et al. have discussed the area of concern when making credit risk prediction models among SMEs that are utilized in supply chain finance [24]. The authors present a proposal of a new research in which there will be a correlation between demographics and behavioral data in order to improve credit risk prediction. A simulation of machine-learning algorithms was implemented by the researchers in a series of experiments which has turned out to be significant. The combination of both demographic and behavioral data improved at an average rate of 15 percent with regard to their prediction quality. Also, the precision-recall trade-off increased by an average of 12 percent and this is a sign of the many benefits that come with combining data. The statistical data aids in the understanding of why it is effective to use multiple pieces of data when it comes to predicting credit risk and, as a result, possible application in various decisions related to lending in the supply chain finance realm. Our work differs in both scope and methodology; instead of fusing demographic and behavioral data for credit risk assessment, we use sector-level economic indicators and a hybrid CNN–LSTM approach to model complex patterns in SMEs' contribution to national economic growth.

3. Material and Method

This section discusses the methodology for applying a hybrid model to estimate the contribution of SMEs to the economy. This methodology is based on a study on SMEs in Türkiye, provided by the Turkish Statistical Institute (TURKSTAT), using data collected between 2009 and 2020. To develop a new, combined model, CNN and LSTM were used as inputs to a specific methodological study. CNN and LSTM are deep learning networks known for handling spatial and temporal data characteristics and, therefore, are more predictable. In this section, we will explain how we collected and processed the data to develop our hybrid model and provide more information about the technical model before moving on to the prediction.

3.1. Dataset

In this study, SME data for the years 2009-2020 presented by TURKSTAT were used. The number of SMEs, employees, salaries, wholesale purchasing cost of goods and services, and personnel costs were taken as inputs. Turnover, added value per employee, production value, factor cost, and added value attributes are taken as output. The dataset consists of scaled input and output preference indexes for 12 years, unscaled general preference index, scaled general preference index, and ranking of contribution to the economy by years. The dataset used consists of data from 14 sectors in the Turkish ecosystem. These sectors are mining and quarrying, production, production and distribution of air conditioning, gas, electricity, and steam, remediation, sewage, and waste management, building, storage, transport, food and accommodation, communication and information, real estate, technical and, scientific, support and administration, education, social and health services, culture, art and entertainment. Due to the small data in the original dataset, data augmentation was made on the table using SMOTE-TS. The original dataset consists of data from 2009 to 2020. Using SMOTE-TS, the total dataset size was increased to 20000. As an example, Figure 3.1 shows the original data for the mining and quarrying sectors.

Figure 3.1 shows the original time series data for the mining and quarrying sector between 2009 and 2020, showing trends in turnover, value added per employee, production value, factor cost, and value added before data enrichment. These values form the basic input for the forecast models. SMOTE-TS is a customized variation of SMOTE to address class imbalance in time series data and increase instances of minority class [25]. Although the traditional SMOTE method was designed for tabular data, its direct application may need help due to the nature and characteristics of time series data [26]. Therefore, SMOTE-TS offers a customized approach for time series data.

Date	Number of SMEs	Number of employees	Salaries	Wholesale purchasing cost of goods	Services and personnel costs	Giro	Value added per employee	Production value	Factor cost and value added attributes
2009	3 963	113 922	112 454	9 267 949 022	2 538 187 447	14 273 424 016	47 726	13 355 790 523	5 437 090 655
2010	4 128	123 639	122 147	12 171 969 825	2 944 436 681	18 583 958 937	58 828	17 629 113 602	7 273 430 033
2011	4 336	133 000	131 527	15 654 579 336	3 422 243 971	24 451 224 519	78 028	23 731 019 998	10 377 769 572
2012	4 523	139 128	137 583	16 755 671 022	3 940 339 764	26 453 368 218	81 462	25 564 942 273	11 333 691 622
2013	4 732	141 057	139 469	19 085 706 933	4 424 777 458	29 285 401 740	85 296	28 385 542 996	12 031 551 345
2014	4 856	138 222	136 544	21 283 527 321	4 983 462 127	29 920 016 087	74 620	28 539 758 792	10 314 126 339
2015	4 645	131 456	129 943	21 641 633 374	5 393 404 438	29 638 426 627	73 368	28 130 290 122	9 644 665 403
2016	4 793	125 879	124 336	22 641 169 523	6 075 702 034	31 163 777 308	84 027	29 501 292 638	10 577 236 296
2017	4 911	132 532	130 960	28 292 231 626	7 033 055 775	41 711 795 553	117 436	38 923 081 826	15 564 009 356
2018	5 079	135 263	133 680	38 957 909 181	8 278 970 101	56 899 230 284	164 395	54 886 448 006	22 236 560 241
2019	5 079	127 520	125 929	45 757 713 342	9 781 214 631	67 542 936 906	205 008	65 342 734 120	26 142 653 046
2020	5 009	124 054	122 503	54 907 577 635	10 784 260 803	85 599 215 308	293 181	83 150 130 997	36 370 278 151
2021	5 127	133 003	131 435	83 297 674 835	14 239 886 095	134 926 091 129	462 402	131 481 033 410	61 500 791 283

Figure 3.1: The original data for the mining and quarrying sectors.

The primary purpose of SMOTE-TS is to increase the sample size of the minority class while at the same time preserving the structure and properties of the time series data. When generating synthetic samples, this method considers relationships and patterns within the time series. Unlike traditional SMOTE, SMOTE-TS reproduces time series data while generating synthetic samples to better reflect relationships and dynamics over time. The basic steps of SMOTE-TS are:

- Selecting time series examples: Time series examples belonging to the minority class are selected.
- Splitting time series samples: Selected samples are split into parts within the time series.
- Finding k-nearest neighbors between samples: Selecting time series examples: Examples from the minority class are selected.
- Generation of synthetic samples: For each subsequence, synthetic samples are generated among the k-nearest neighbors. These generated synthetic samples are similar to the existing subsequence.
- Combining augmented data: The generated augmented data are added to the original subsequences, thus creating new augmented time series data.
- Since SMOTE-TS is a specialized method to preserve the dynamics and properties of time series data.

The application of SMOTE-TS in this study aimed to address the limited size and class imbalance of the original dataset by generating synthetic time series samples. Empirical results indicated that this augmentation contributed to improved model accuracy across all tested algorithms, with the most notable gains observed in deep learning models such as CNN–LSTM, where richer and more balanced training data enhanced the ability to learn temporal and spatial patterns. However, synthetic data generation can potentially increase the risk of overfitting, as the model may learn patterns that are artifacts of the augmentation process rather than genuine characteristics of the original data. To minimize this risk, we employed techniques such as early stopping, dropout regularization, and evaluation on an untouched test set. The observed improvements in test performance suggest that, in our case, SMOTE-TS enhanced generalization rather than causing overfitting, but caution should be exercised when applying it to datasets with highly complex temporal dependencies. In this study, SMOTE-TS was implemented in Python 3.9 using the imblearn library's customized time-series oversampling functionality. The augmentation process involved: Selecting minority class sequences from the dataset, splitting each sequence into fixed-length subsequences (window size = 12), identifying k-nearest neighbors within the temporal feature space (k = 5), generating synthetic samples by interpolating between each subsequence and its selected neighbors while preserving the temporal order of features, and combining synthetic and original sequences to form the augmented dataset. For consistency, all variables were scaled using MinMaxScaler prior to oversampling, and the generated synthetic sequences were incorporated only into the training set to avoid data leakage. These steps ensured that the augmentation process respected temporal dependencies and could be fully replicated by other researchers using the same parameter settings.

3.2. Baseline Models

LR aims to establish a linear equation that best fits the observed data points [27]. This method utilizes the independent variables to predict the value of the dependent variable through a linear equation [28]. The slope and intercept are adjusted during training to ensure the line fits the data optimally. LR is widely used in various fields for tasks such as predicting stock prices, estimating sales trends, and analyzing the impact of variables on outcomes [29].

Random Forest (RF) creates multiple decision trees during training and then combines their predictions to produce a more robust and accurate final result [30]. Every decision tree is trained on a subset randomly selected. This is meant to avoid overfitting The main advantage of the algorithm is the possibility to reflect the complicated relations in the dataset and studying high-dimensional data [31]. A forest, in prediction, has each of the trees in the forest making its own prediction and the mode (in classification) or the mean (in regression) prediction by the trees is the final prediction outcome. The application of RF is wide-ranged, and is used in various fields, including financial, health, and image processing areas since it can deal with outliers and noise as well as non-linear relationships [32]. The fact that it is simple and robust, makes it a favorite in a wide range of issues that a certain degree of accuracy and convenience of interpretation is suitable.

The Support Vector Regression (SVR) is a machine learning method of optimal regression analysis. SVR is a modification of Support Vector Machines (SVM) that was developed to work in a classification, as opposed to a forecasting situation involving continuous numbers [33]. The SVR process is concerned with obtaining a function format that provides the best approximation to the training dataset function, similarly with regulating the mutual margin of error or the bulk of the permissible range of error. During SVR, a tolerable level of error is applied in the process of determining the ideal fit of the training information. Unlike SVM, SVR focuses on minimizing the extent of error and variance in the creation and expression of the data distribution, allowing for a ranked degree of ill-fitting or error [34]. Once a hyperplane has been chosen to provide the most significant margin of separation surrounding it, all of the data points that fall into that margin are therefore pertinent as support vectors. The ones that are going to surpass this error margin will affect the hyperplane, hence, its position and orientation. In terms of concept, this is achieved within SVR through the use of Kernel functions, which alter the data, thereby allowing it to be represented in a higher dimension. This architecture will enable it to learn non-linear associations with all features and the target value, while maintaining the error margin as specified above [35]. The characteristic of the kernel used in SVR may differ based on the kind of data-shaped relationship that one uses.

CNN Regression is a machine-learning approach for predicting continuous numerical values [36]. It is an application of CNN, which is renowned for its effectiveness in tasks such as image recognition and regression problems. In CNN Regression, the architecture and principles of CNNs are adapted to perform regression tasks. Traditional CNNs are designed for classification, where the output is a class label [37]. There is a basic form of Continuous Neural Network Regression that involves convolutional, pooling, and fully connected layer types. Convolutional layers focus on localized patterns in the input data, pooling layers compress the data while preserving essential features, and fully connected layers aggregate all features to formulate predictions [38].

CNN Regression enables professionals to utilize a proposed architecture to predict continuous values based on data that exhibits identifiable spatial patterns/structures. For example, stock prices curve over time based on their feature space, an age estimator based on facial curves and angles relative to a reference standard, and energy consumption forecasts. The CNN Regression harnesses the architectural advantage of convolutional neural networks, particularly in simultaneously capturing hierarchical and spatial relationships, thereby propitiating a robust and precise application that establishes a continuum from CNNs to regression predictions [39].

LSTM Regression utilizes its fundamental ability to capture long-range dependencies and chronological patterns in sequential data to make precise predictions for continuous values [40]. Unlike feedforward neural networks, LSTM uses memory cells and gates to maintain information from long sequences of data [41]. Since LSTMs are well-suited for representing time series data or any data with temporal relationships, in regression, the LSTM model is used to capture relationships among features and the response variable while preserving the order of the data points. The architecture of LSTM Regression comprises LSTM layers and fully connected layers to facilitate prediction. The LSTM layers will take in the sequential input data and remember relevant trends, patterns, and dependencies from sequential data. The fully connected layer will then build upon this information to predict the continuous output [42].

3.3. Developed Hybrid Model

Developed hybrid model is a compelling architecture for predicting time series data in regression problems. This model combines the capabilities of CNN and LSTM models. The primary objective is to synergize CNN's ability to capture structural features with LSTM's proficiency in retaining long-term dependencies, thus achieving more accurate predictions. The developed hybrid model is shown in Figure 3.2.

Figure 3.2 shows the architecture of the proposed CNN-LSTM hybrid model. The model first applies a Conv1D layer to capture local spatial patterns in time series data, followed by LSTM layers to learn long-term temporal

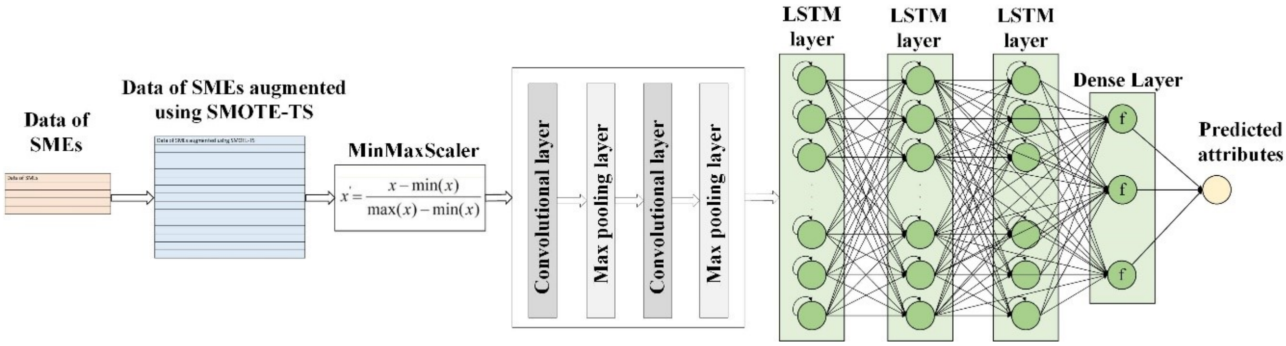

Figure 3.2: The developed hybrid model.

dependencies. The figure shows the sequential processing flow from input features to the final output layer. The developed model comprises the following steps:

• Data Preparation: In the initial step, data related to the contributions of SMEs to the economy is collected and organized. This data typically includes economic indicators, employment figures, trade volume, and other relevant factors. The data were scaled using MinMaxScaler. MinMaxScaler is a pre-processing technique that often scales and normalizes data in a specific range [0, 1]. It transforms the original features by preserving their proportions, helping in better performance of machine learning algorithms. This scaling process ensures data falls within a defined range, preventing issues like data values causing algorithm bias.

• Partitioning of Data: It was decided to partition the data into discrete subset to carry out the process of model development and evaluation. In particular, 80-20 percent were used in training and testing respectively. In the training set, there was another split where 90 percent of data were used to train a model and 10 percent were used to validate the model. The validation subset was more important in adjusting the model parameters, and that increased its performance.

• CNN Stage: The time series data input is passed through CNN layer. The CNN picks out the periodicities, fluctuations and the points of transformation in the data.

• LSTM Stage: LSTM constitutes an additional stage into which the result of the CNN stage is submitted. The LSTM can use the past timeframes of the data in making predictions of the future trends and variations in the economy. It is particularly useful in the analysis of the long run impacts of the SMEs on the economy.

• General Prediction: The LSTM stage is leveraged to test its output as the estimation of SMEs contribution to the economy. Such a forecast may centre on economic growth, job creation, the amount of trade, or any other aspect that SMEs affect.

• Model Training and Evaluation: The training of the model is done by minimizing the errors on the training data.

• Prediction and Assessment: After the training is done, the model can be used to make new data predictions. It is evaluated in terms of its predictive capacity through evaluation of the predicted economic data versus actual economic indicators.

GridSearchCV was used to determine the hyperparameters of the models being applied. It aims to find the optimal combination of hyperparameters that results in the best performance for the model on a validation dataset [43]. The outcome of GridSearchCV is the combination of hyperparameters that yields the highest validation performance. This combination can then train the final model on the entire training dataset. GridSearchCV automates the hyperparameter tuning process, helping practitioners avoid manual trial and error and potentially leading to more optimal model configurations [44]. Parameters used for Conv1D CNN are filters=32, kernel size=1, and activation= Rectifier Linear Unit (ReLU). In the MaxPooling1D layer, the pool size is 2. A total of 64 neurons were used in the three LSTM layers. ReLU was used as the activation function, and Adam was used for optimization. The epoch number is 100, and the batch size is 256. For fair comparison, all baseline models were optimized using GridSearchCV with 5-fold cross-validation on the training set. The optimal hyperparameter configurations obtained are as follows:

Random Forest (RF): Number of estimators = 300, maximum depth = 20, minimum samples split = 2, criterion = 'mse'.
Support Vector Regression (SVR): Kernel = 'rbf', C = 100, gamma = 0.01, epsilon = 0.1.
Multi-Layer Perceptron (MLP): Hidden layers = (128, 64, 32), activation = 'relu', solver = 'adam', learning rate = 0.001, max iterations = 500, batch size = 64.
Convolutional Neural Network (CNN): Conv1D filters = 64, kernel size = 2, activation = 'relu', pooling size = 2, dropout rate = 0.3, fully connected layer neurons = 64, optimizer = 'adam', learning rate = 0.001, batch size = 256, epochs = 100.
Long Short-Term Memory (LSTM): Units = 64, dropout rate = 0.3, recurrent dropout = 0.2, activation = 'tanh', optimizer = 'adam', learning rate = 0.001, batch size = 256, epochs = 100.

4. The Experimental Results

In this study, the values of turnover, added value per employee, production value, factor cost and added value attributes were predicted for 14 different sectors. The comparative analysis of experimental outcomes encompassed the evaluation of each model's performance through metrics including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2. To evaluate the predictive performance of the models, three commonly used regression metrics were employed.
RMSE: Measures the square root of the average of squared differences between predicted and actual values. It penalizes larger errors more heavily, making it useful for identifying models that minimize large deviations.
MAE: Calculates the average absolute difference between predicted and actual values, providing an interpretable measure of average prediction error in the same units as the target variable.
R^2: Represents the proportion of variance in the dependent variable explained by the model. An R^2 value closer to 1 indicates a better fit between predicted and observed data. These metrics were selected because they offer complementary perspectives on performance.
RMSE and MAE assess prediction accuracy from different sensitivity angles, while R^2 evaluates the explanatory power of the model. In the context of economic data analysis, these measures provide a balanced view of both the magnitude of prediction errors and the overall model fit. The experimental results for the mining and quarrying sector are shown in Table 4.1.

Table 4.1: The experimental results for the mining and quarrying sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
Turnover	RMSE	918017.33	891833.58	886574.16	855130.99	870852.58	603277.34	566285.37
	MAE	791936.38	739531.09	702847.39	676743.39	681885.27	477504.65	466900.90
	R^2	0.819	0.831	0.839	0.845	0.844	0.889	0.893
Added value per employee	RMSE	9745.63	9611.78	9575.53	9315.26	9539.65	9116.60	8684.91
	MAE	6910.94	6825.45	6782.23	6638.98	6755.79	6462.10	6139.31
	R^2	0.833	0.842	0.847	0.866	0.850	0.901	0.912
Production value	RMSE	2729202.46	2716051.86	2705550.59	2696247.11	2747058.82	2651986.68	2615558.74
	MAE	2385525.11	2363971.06	2354152.15	2345842.95	2395621.40	2137194.65	2113074.20
	R^2	0.820	0.827	0.829	0.856	0.834	0.891	0.901
Factor cost and added value	RMSE	427704.63	415590.99	412795.54	289955.90	396789.24	274836.91	257974.50
	MAE	369000.07	344772.80	327534.16	310689.16	315420.52	217755.74	212744.63
	R^2	0.852	0.860	0.868	0.875	0.872	0.891	0.899

Experimental results for the mining and quarrying are presented in Table 1. As depicted in Table 1, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the production sector are shown in Table 4.2.

Experimental results for the production are presented in Table 4.2. As depicted in Table 4.2, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the production and distribution of electricity, gas, steam and air conditioning sector are shown in Table 4.3.

Table 4.2: The experimental results for the production sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
	RMSE	3569185.28	3460322.25	3444768.62	3322183.89	3382562.25	2345242.92	2202046.56
	MAE	3071521.47	2877120.34	2733265.51	2628289.51	2643841.04	1856538.07	1815699.49
	R^2	0.826	0.841	0.852	0.859	0.861	0.898	0.904
	RMSE	4997.43	4925.60	4910.21	4874.29	4771.81	4669.36	4464.01
Added value per employee	MAE	3540.27	3488.96	3478.70	3463.31	3386.35	3309.44	3129.96
	R^2	0.838	0.846	0.849	0.853	0.870	0.905	0.915
	RMSE	101398423.81	100915397.24	100506682.45	100135127.63	102067229.83	98537420.28	97188385.33
Production value	MAE	88616797.65	87687900.41	87316341.50	87130562.05	88988356.55	79402136.93	78510395.57
	R^2	0.823	0.828	0.832	0.860	0.838	0.894	0.906
	RMSE	7845740.35	7621932.87	7570568.81	7278903.60	5317925.65	5040931.22	4730917.60
Factor cost and added value	MAE	6768937.28	6323176.82	6007662.93	5697646.42	5778360.07	3993488.83	3901768.80
	R^2	0.862	0.866	0.870	0.903	0.898	0.915	0.921

Table 4.3: The experimental results for the production and distribution of electricity, gas, steam and air conditioning sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
	RMSE	91026671.54	90459633.24	88973655.65	85423478.23	87651464.78	81207381.85	76186019.39
Turnover	MAE	72510311.63	71967854.11	69326547.37	66473211.45	68127479.89	64273282.42	62853466.96
	R^2	0.821	0.832	0.849	0.867	0.862	0.881	0.889
	RMSE	7185.68	7082.15	7046.22	7010.25	6859.26	6715.46	6419.23
Added value per employee	MAE	5090.52	5017.18	5002.80	4975.48	4860.44	4745.40	4499.50
	R^2	0.861	0.866	0.870	0.879	0.874	0.885	0.892
	RMSE	62514440.81	62216644.26	61964662.14	61735590.01	62926774.96	60727496.91	59918865.59
Production value	MAE	54634277.43	54061590.62	53832305.79	53717979.03	54863316.89	48951911.22	48403205.91
	R^2	0.871	0.875	0.879	0.889	0.883	0.895	0.889
	RMSE	5016437.23	4870966.63	4840720.10	4641700.36	3440565.85	3224094.40	3046562.04
Factor cost and added value	MAE	4322437.79	4037788.52	3836310.74	3638343.97	3689885.16	2550120.45	2491550.36
	R^2	0.858	0.861	0.864	0.871	0.866	0.879	0.883

Experimental results for the production and distribution of electricity, gas, steam and air conditioning sector are presented in Table 4.3. As depicted in Table 4.3, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the sewage, waste management and remediation activities sector are shown in Table 4.4.

Table 4.4: The experimental results for the sewage, waste management and remediation activities sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
	RMSE	90241569.33	89679422.34	88206261.54	84686703.35	86895474.12	80506971.65	75528917.96
Turn over	MAE	71884912.47	71347134.16	68728608.36	65899882.23	67539882.49	63718927.79	62311358.13
	R^2	0.828	0.839	0.856	0.874	0.869	0.888	0.896
	RMSE	5875.42	5790.43	5761.67	5732.33	5608.05	5490.81	5248.52
Added value per employee	MAE	4162.68	4102.39	4090.01	4068.55	3974.47	3880.63	3679.66
	R^2	0.884	0.890	0.895	0.905	0.899	0.911	0.914
	RMSE	61590582.32	61297186.47	61048928.26	60823241.06	61996822.24	59830046.61	59033365.68
Production value	MAE	53826874.15	53262650.10	53036754.40	52924117.62	54052528.60	48228483.53	47687887.41
	R^2	0.856	0.859	0.861	0.869	0.865	0.873	0.878
	RMSE	3664307.03	3558047.56	3535953.31	3390577.02	2513196.04	2355072.48	2225392.38
Factor cost and added value	MAE	3157368.14	2949443.72	2802272.46	2657665.44	2695314.25	1862761.07	1819978.93
	R^2	0.907	0.910	0.915	0.923	0.920	0.929	0.934

Experimental results for the sewage, waste management and remediation activities sector are presented in Table 4.4. As depicted in Table 4.4, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the building sector are shown in Table 4.5.

Experimental results for the building sector are presented in Table 4.5. As depicted in Table 4.5, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the transport and storage sector are shown in Table 4.6.

Table 4.5: The experimental results for the building sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
Turnover	RMSE	75076180.22	74608504.63	73382913.40	70454828.91	72292407.17	66977513.01	62836038.90
	MAE	59804419.16	59357016.21	57178542.87	54825193.03	56189586.52	53010755.13	51839732.06
	R^2	0.911	0.913	0.917	0.927	0.921	0.931	0.936
Added value per employee	RMSE	6121.60	6033.04	6003.08	5972.51	5843.02	5720.87	5468.43
	MAE	4337.09	4274.28	4261.38	4239.02	4141.65	4043.22	3833.83
	R^2	0.852	0.855	0.857	0.865	0.861	0.869	0.873
Production value	RMSE	49992355.92	49754209.03	49552701.66	49369513.09	50322095.45	48563349.18	47916692.76
	MAE	43690644.89	43232670.71	43049313.45	42957887.32	43873805.82	39146496.57	38707700.60
	R^2	0.851	0.854	0.855	0.863	0.860	0.869	0.873
Factor cost and added value	RMSE	4202960.16	4081081.23	4055738.97	3888992.89	2882636.33	2701268.77	2552525.64
	MAE	3621501.25	3383012.20	3214207.81	3048342.42	3091525.01	2136587.96	2087516.59
	R^2	0.861	0.865	0.869	0.875	0.871	0.879	0.884

Table 4.6: The experimental results for the transport and storage sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
Turnover	RMSE	90091416.26	89530206.96	88059496.56	84545795.11	86750889.58	80373016.38	75403247.12
	MAE	71765302.99	71228419.89	68614251.47	65790232.07	67427504.72	63612906.21	62207678.77
	R^2	0.875	0.877	0.880	0.887	0.884	0.890	0.894
Added value per employee	RMSE	7823.40	7710.22	7671.93	7632.86	7467.38	7311.27	6988.65
	MAE	5542.80	5462.53	5446.04	5417.46	5293.02	5167.23	4899.63
	R^2	0.858	0.861	0.863	0.871	0.867	0.873	0.878
Production value	RMSE	61385613.83	61093193.79	60845762.94	60620825.33	61790501.11	59630936.76	58836907.12
	MAE	53647742.86	53085396.67	52860252.47	52747990.07	53872646.23	48067983.34	47529186.47
	R^2	0.873	0.876	0.879	0.884	0.881	0.887	0.890
Factor cost and added value	RMSE	5514283.73	5354379.59	5321130.03	5102359.42	3782019.91	3544065.01	3348914.85
	MAE	4751409.64	4438512.82	4217041.27	3999425.36	4056081.87	2803203.19	2738822.21
	R^2	0.876	0.879	0.881	0.886	0.883	0.890	0.894

Experimental results for the transport and storage sector are presented in Table 4.6. As depicted in Table 4.6, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the accommodation and food service sector are shown in Table 4.7.

Table 4.7: The experimental results for the accommodation and food service sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
Turn over	RMSE	82200197.74	81688145.10	80346255.39	77140324.70	79152271.51	73333044.71	68798583.37
	MAE	65479291.91	64989434.77	62604244.61	60027584.62	61521445.16	58040972.06	56758830.81
	R^2	0.891	0.893	0.895	0.901	0.898	0.903	0.906
Added value per employee	RMSE	6791.17	6692.77	6659.43	6625.15	6482.97	6346.22	6066.65
	MAE	4811.31	4741.56	4727.07	4702.64	4594.10	4485.54	4253.74
	R^2	0.884	0.887	0.889	0.893	0.891	0.895	0.898
Production value	RMSE	55754417.81	55488822.23	55264089.46	55059786.35	56122162.76	54160705.02	53439516.77
	MAE	48726378.14	48215619.49	48011128.70	47909164.54	48930650.69	43658477.48	43169106.18
	R^2	0.884	0.888	0.890	0.896	0.893	0.899	0.902
Factor cost and added value	RMSE	4553496.53	4421453.88	4393996.36	4213343.51	3123055.14	2926560.01	2765412.81
	MAE	3923542.19	3665163.47	3482280.97	3302580.87	3349365.71	2314783.96	2261620.27
	R^2	0.890	0.892	0.895	0.900	0.897	0.903	0.906

Experimental results for the accommodation and food service sector are presented in Table 4.7. As depicted in Table 4.7, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the information and communication sector are shown in Table 4.8.

Experimental results for the information and communication sector are presented in Table 4.8. As depicted in Table 4.8, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the real estate sector are shown in Table 4.9.

Experimental results for the real estate sector are presented in Table 4.9. As depicted in Table 4.9, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the professional, scientific and technical sector are shown in Table 4.10.

Table 4.8: The experimental results for the information and communication sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
Turnover	RMSE	85899206.64	85364112.74	83961837.11	80611639.03	82714124.88	76633032.19	71894520.23
	MAE	68425860.05	67913959.68	65421436.56	62728826.47	64289910.07	60652816.74	59312978.61
	R^2	0.883	0.887	0.890	0.895	0.892	0.898	0.902
Added value per employee	RMSE	6804.75	6706.15	6672.74	6638.43	6495.93	6358.91	6078.78
	MAE	4820.93	4751.04	4736.52	4712.05	4603.28	4494.51	4262.24
	R^2	0.895	0.898	0.900	0.906	0.903	0.910	0.913
Production value	RMSE	58263366.61	57985819.62	57750973.96	57537477.37	58647660.54	56597937.13	55844295.87
	MAE	50919065.16	50385322.01	50171629.45	50065077.40	51132530.71	45623109.21	45111716.72
	R^2	0.895	0.898	0.901	0.907	0.903	0.910	0.914
Factor cost and added value	RMSE	5070773.73	4923731.31	4893154.85	4691979.07	3477834.78	3259017.41	3079564.35
	MAE	4369256.58	4081526.44	3877868.12	3677754.76	3729854.67	2577743.04	2518540.24
	R^2	0.883	0.886	0.889	0.895	0.892	0.898	0.902

Table 4.9: The experimental results for the real estate sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
Turnover	RMSE	87703089.98	87156759.74	85725036.73	82304483.20	84451122.41	78242326.37	73404305.03
	MAE	69862803.11	69340153.32	66795287.86	64046132.16	65639998.95	61926526.51	60558551.61
	R^2	0.881	0.884	0.887	0.892	0.890	0.896	0.900
Added value per employee	RMSE	8029.60	7913.25	7873.83	7833.34	7665.19	7503.51	7172.96
	MAE	5688.69	5606.22	5589.09	5560.21	5431.87	5303.52	5029.44
	R^2	0.875	0.879	0.882	0.890	0.886	0.892	0.895
Production value	RMSE	82733980.59	82339864.32	82006383.03	81703218.60	83279678.18	80369071.06	79298900.98
	MAE	72305072.53	71547157.14	71243714.27	71092410.42	72608194.73	64784815.86	64058638.40
	R^2	0.883	0.886	0.890	0.897	0.893	0.901	0.905
Factor cost and added value	RMSE	6794836.79	6597800.51	6556827.34	6287252.77	4660299.94	4367083.03	4126616.14
	MAE	5854803.81	5469245.24	5196343.18	4928191.60	4998005.79	3454176.27	3374844.90
	R^2	0.880	0.882	0.885	0.891	0.888	0.894	0.898

Table 4.10: The experimental results for the professional, scientific and technical sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
Turn over	RMSE	55861840.14	55513859.22	54601934.80	52423237.84	53790523.49	49835876.50	46754334.06
	MAE	44498600.97	44165702.74	42544769.36	40793714.46	41808916.38	39443647.73	38572325.25
	R^2	0.883	0.886	0.888	0.895	0.891	0.898	0.903
Added value per employee	RMSE	7669.17	7558.84	7520.66	7481.02	7321.23	7166.58	6850.49
	MAE	5433.45	5354.91	5338.87	5310.41	5188.37	5065.05	4803.65
	R^2	0.882	0.887	0.890	0.896	0.893	0.899	0.902
Production value	RMSE	80637407.13	80253279.07	79928248.35	79632766.25	81169276.99	78332427.04	77289377.46
	MAE	70472780.52	69734071.48	69438318.76	69290848.72	70768220.11	63143095.51	62435320.27
	R^2	0.891	0.895	0.900	0.906	0.902	0.910	0.914
Factor cost and added value	RMSE	6320778.74	6137488.29	6099374.08	5848607.94	4335162.53	4062402.62	3838712.23
	MAE	5446329.20	5087669.43	4833807.36	4584364.71	4649307.41	3213187.06	3139390.14
	R^2	0.871	0.875	0.878	0.885	0.881	0.890	0.894

Experimental results for the professional, scientific and technical sector are presented in Table 4.10. As depicted in Table 4.10, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the administrative and support services sector are shown in Table 4.11.

Table 4.11: The experimental results for the administrative and support services sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
Turn over	RMSE	52403227.23	52076791.77	51221327.35	49177521.13	50460153.27	46750353.54	43859600.30
	MAE	41743528.39	41431240.90	39910665.78	38268024.01	39220371.69	37001545.81	36184170.07
	R^2	0.887	0.890	0.893	0.899	0.895	0.902	0.906
Added value per employee	RMSE	8459.09	8337.40	8295.28	8251.56	8075.31	7904.73	7556.09
	MAE	5993.09	5906.46	5888.77	5857.38	5722.77	5586.75	5298.42
	R^2	0.880	0.884	0.887	0.892	0.890	0.895	0.899
Production value	RMSE	75221461.87	74863133.17	74559933.26	74284296.65	75717609.29	73071293.61	72098299.99
	MAE	65739534.74	65050439.33	64774551.47	64636985.49	66015130.08	58902141.52	58241903.07
	R^2	0.870	0.872	0.876	0.883	0.880	0.886	0.890
Factor cost and added value	RMSE	6346061.85	6162038.77	6123772.58	5872002.34	4352503.86	4078652.74	3854067.44
	MAE	5468114.51	5108020.62	4853143.46	4602702.11	4667905.90	3226040.26	3151948.12
	R^2	0.864	0.867	0.870	0.877	0.874	0.880	0.883

Experimental results for the administrative and support services sector are presented in Table 4.11. As depicted in Table 4.11, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the education sector are shown in Table 4.12.

Table 4.12: The experimental results for the education sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
Turnover	RMSE	48120502.09	47820745.97	47035194.64	45158421.28	46336228.96	42929617.41	40275115.72
	MAE	38331981.15	38045216.84	36648912.76	35140517.33	36015033.40	33977544.32	33226969.32
	R^2	0.877	0.880	0.882	0.889	0.885	0.892	0.897
Added value per employee	RMSE	5323.37	5246.94	5220.89	5192.67	5082.90	4974.52	4755.29
	MAE	3771.86	3717.76	3705.31	3686.23	3601.16	3515.81	3334.13
	R^2	0.881	0.883	0.886	0.895	0.891	0.898	0.902
Production value	RMSE	69973452.17	69640123.85	69358077.16	69101671.96	70434985.24	67973296.85	67068186.06
	MAE	61153055.91	60512036.40	60255396.32	60127428.57	61409423.41	54792689.10	54178514.70
	R^2	0.879	0.882	0.885	0.893	0.889	0.896	0.901
Factor cost and added value	RMSE	5581408.16	5419559.26	5385903.91	5164469.78	3828059.17	3587205.25	3389681.20
	MAE	4809247.80	4492542.49	4268375.15	4048110.03	4105458.36	2837326.01	2772161.91
	R^2	0.887	0.891	0.895	0.900	0.897	0.902	0.906

Experimental results for the education sector are presented in Table 4.12. As depicted in Table 4.12, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the human health and social services sector are shown in Table 4.13.

Table 4.13: The experimental results for the human health and social services sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
Turn over	RMSE	56493469.45	56141556.11	55219319.65	53015987.96	54398733.06	50399371.14	47282986.01
	MAE	45001745.87	44665085.23	43025824.82	41254967.20	42281649.77	39889637.80	39008462.64
	R^2	0.875	0.877	0.880	0.887	0.884	0.890	0.894
Added value per employee	RMSE	7718.88	7608.06	7570.29	7529.37	7370.20	7213.05	6895.17
	MAE	5469.19	5390.75	5372.70	5345.03	5221.68	5097.92	4834.48
	R^2	0.870	0.874	0.877	0.885	0.880	0.888	0.892
Production value	RMSE	82288779.75	81896786.33	81565099.91	81263566.15	82831543.85	79936597.55	78872187.42
	MAE	71915993.45	71162155.27	70860346.06	70709856.74	72217482.47	64436202.58	63713933.39
	R^2	0.877	0.880	0.882	0.890	0.886	0.895	0.902
Factor cost and added value	RMSE	6362805.30	6178298.74	6139930.28	5887496.30	4363987.90	4089414.09	3864237.74
	MAE	5482542.49	5121498.11	4865948.61	4614845.65	4680223.84	3234552.27	3160265.60
	R^2	0.890	0.893	0.896	0.902	0.899	0.914	0.918

Experimental results for the human health and social services sector are presented in Table 4.13. As depicted in Table 4.13, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. The experimental results for the culture, art and entertainment sector are shown in Table 4.14. Ex-

Table 4.14: The experimental results for the culture, art and entertainment sector.

Feature	Metric	LR	RF	SVR	MLP	CNN	LSTM	CNN-LSTM
Turnover	RMSE	68922032.73	68492698.11	67367570.86	64679505.03	66366454.39	61487233.70	57685243.56
	MAE	54902129.96	54491404.74	52491506.95	50331060.62	51583613.21	48665358.13	47590324.47
	R^2	0.883	0.888	0.891	0.897	0.895	0.900	0.906
Added value per employee	RMSE	12496.86	12317.45	12256.30	12190.05	11932.35	11677.93	11163.28
	MAE	8854.61	8727.62	8698.40	8653.60	8453.90	8253.53	7827.02
	R^2	0.883	0.886	0.890	0.900	0.895	0.902	0.907
Production value	RMSE	101215199.10	100733047.25	100325073.86	99954186.03	101882798.90	98322015.45	97012791.14
	MAE	88456671.94	87529451.97	87158226.43	86973124.88	88827503.74	79256529.31	78368138.78
	R^2	0.901	0.906	0.910	0.920	0.914	0.925	0.931
Factor cost and added value	RMSE	9480579.90	9205664.02	9148495.71	8772369.41	6502340.63	6093227.10	5757713.65
	MAE	8168988.31	7631032.04	7250262.56	6876119.98	6973532.27	4819482.31	4708795.47
	R^2	0.875	0.878	0.881	0.890	0.885	0.894	0.899

perimental results for the culture, art and entertainment sector are presented in Table 4.14. As depicted in Table 4.14, the hybrid model that was devised exhibits superior performance in comparison to the other evaluated models. Figure 4.1 shows the R^2 values of the compared models for each sector.

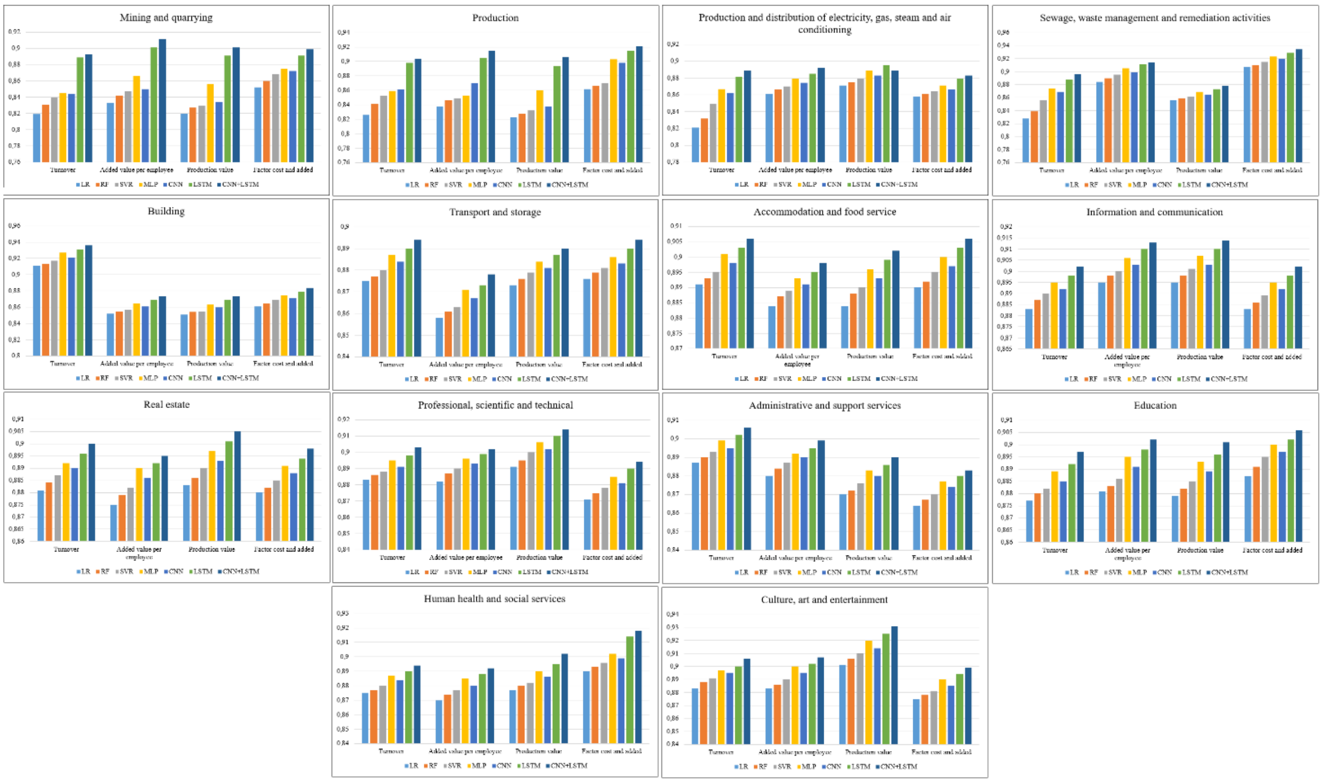

Figure 4.1: The R^2 values of the compared models for each sector.

Figure 4.1 shows the comparison of R^2 values for all models evaluated (LR, RF, SVR, MLP, CNN, LSTM, and CNN–LSTM) across the 14 economic sectors considered in this study. Higher R^2 values indicate better predictive performance, with the CNN–LSTM model outperforming other methods across all sectors.

As can be seen in Figure 4.1, the hybrid model developed for each sector and attribute has a higher R^2 value than the other models. The remainder of this section discusses why each model compared outperforms the other. The fact that RF is more successful than LR can be attributed to the fact that time series data often contain nonlinear models and complex relationships. Excels at capturing these nonlinearities, whereas LR assumes linear relationships. RF's flexibility can lead to better results in time series prediction scenarios involving multiple variables.

RF combines multiple decision trees, making it more resistant to overfitting. Overfitting is a common issue in time series analysis, and RF's ensemble nature can mitigate this problem. The fact that SVR is more successful than RF can be interpreted as an indication of SVR's effectiveness in capturing nonlinear relationships in time series data. SVR is more effective, especially when the underlying patterns are complex and not easily captured by linear methods such as RF. SVR can implicitly map data into a higher-dimensional space, enabling the discovery of intricate relationships that RF might struggle to uncover.

The fact that MLP is more successful than SVR can be interpreted by the fact that MLP automatically learns hierarchical feature representations from the data. Due to its layered nature, MLP naturally considers sequential information, enabling it to understand temporal dependencies in time series that SVR may not inherently account for. The fact that MLP is more successful than CNN can be interpreted as MLP can learn hierarchical features from data and extract abstract representations of models at various time scales. Though powerful in image analysis, CNN may not be as good at discerning such hierarchies over time series. MLP is more relaxed with the irregularly spaced and variable-length sequences. CNNs are generally geared towards fixed-sized inputs and may need to be further modified to handle time steps of differing lengths effectively.

The advantages of LSTM over MLP can be attributed to the fact that LSTM is capable of capturing long-term dependencies in ordinal data. LSTM has been designed to model and maintain patterns over long stretches, which aids in the conceptualization of tendencies, seasonality, and complex time series patterns. LSTM is less susceptible to the vanishing gradient phenomenon that may occur when using deeper neural networks, like MLP, and thereby impairs the formation of long-range dependencies. This would be a natural property of LSTM, and LSTM does not have this gradient problem, as it is gated. The other advantage is that LSTM can be used to process sequences of any length, unlike MLP, which has fixed-size inputs. The advantage of using this feature is that it can be applied to time series data with unequally spaced observations.

The reason behind the successful hybrid CNN-LSTM model is that it leverages the advantages of both networks combined. LSTM is better at handling time series data, while CNN excels at spatial patterns. The combination of capabilities allows the hybrid model to detect both the local and long-range temporal patterns simultaneously. The fundamental purpose, as intended by CNN, is that it can be effectively used to learn features of sequential data; thus, it is the most crucial part of pattern recognition on time series. The CNN-LSTM hybrid model can take advantage of the CNN model because it helps outline the visual features of the raw data presented as inputs prior to the LSTMs.

The hierarchical nature of the CNN-LSTM model enables it to create hierarchies of representations for the data in question, as different distinctive features of the data pass through the model's hierarchical structure. The lower-level features are interpreted to mean that CNN layers operate at a deeper level of data abstraction. The LSTM layers, on the other hand, are used to help comprehend high-level representations and abstraction. Being able to interpret data as a hierarchical construct enables this model to draw relationships in forms that are typically intractable and difficult in time series data. The hybrid CNN-LSTM model effectively combines both spatial and temporal information within its composition. Its CNN layers eliminate the spatial dimensions between the variables, and LSTM layers express the temporal relationships and the linkages of the provided time series data. Time series data is typically composed of multiple variables that may be related to one another.

The CNN-LSTM hybrid model addresses the complex structures that may be apparent in multivariate data by establishing cross-variable patterns, which would otherwise be undetectable with individual models. The CNN-LSTM model structure can be adopted to minimize overfitting due to the regularization properties of both CNN and LSTM. This is a transitional piece that is essential in time series prediction, where it is crucial to understand the general trends. The hybrid model is a type of learning that acquires adapted features directly from the data itself, which significantly reduces the amount of feature engineering involved and thus contrasts with more common techniques, such as LR, RF, and SVR. In short, when coupled with the hierarchy of reachability of the feature learning structures of deep learning models, the CNN-LSTM hybrid model can learn, extract,

and integrate the patterns of spatiotemporal variety. The CNN-LSTM model is a suitable recommendation for time series prediction tasks. It is capable of extracting more intricate interactions, enabling it to make predictions more accurately than the individual methods (LR, RF, SVR, MLP, CNN, and LSTM), as it considers both underlying spatial relations and time series relations.
The predictive capability of the proposed CNN–LSTM model offers valuable insights for policymakers and public institutions involved in SME development. By accurately estimating SMEs' contribution to key economic indicators such as turnover, added value per employee, and production value, authorities can better design targeted support programs and allocate resources more efficiently. For instance, sectors predicted to experience lower growth can be prioritized for financial incentives, training programs, or innovation support. Moreover, the model's sector-specific performance metrics can guide regional development strategies, ensuring that investment policies are aligned with areas where SMEs have the highest potential impact. From an economic management perspective, these predictive insights enable proactive policy adjustments in response to emerging trends, thereby supporting sustainable growth and resilience in the SME sector.

5. Conclusion

SMEs are very important for world economies. These vibrant and innovative engines of growth have a large potential to become a powerful driver of economic growth, a job creator, and a local developer. The role of SMEs extends beyond the development of an economy to include other areas, such as technological development, entrepreneurship, and social capital. Most SMEs are innovators or sources of new ideas and solutions that drive competition and vibrancy in the market. It will be resilient in the economy because SMEs can withstand market fluctuations or uncertainty, as they can react swiftly. Economies with diversification, characterized by a large SME sector, are usually more robust. They can become major forces driving economic momentum towards sustainability, primarily due to their unique characteristics, which include flexibility and the potential for introducing local and national productivity improvements. Realizing this potential takes one step further in recognizing the role SMEs play in creating employment opportunities, redistributing wealth, and developing a prosperous economy, not forgetting the potential that SMEs hold as sustainable development drivers. In this work, a hybrid deep learning model is suggested to predict the economic contributions of SMEs. We utilized a dataset available from the Turkish Statistical Institute (TUIK) from 2009 to 2020, trained, and evaluated a set of different machine learning and deep learning algorithms, including LR, RF, SVR, MLP, CNN, LSTM, and a hybrid of CNN and LSTM models. The dataset has been augmented using the SMOTE-TS sampling method, which expands the size of time series data points of the minority class. The results were used to compare the precision of model predictions with one another to determine the level of predictability in the hybrid model. The hybrid model produced the best results in predicting the role of SMEs in the economy because of its ability to employ unique spatial and sequential analysis through CNN and LSTMs. In most cases, our research indicates that deep learning can help us identify complex relationships among economic variables, as well as enhance the predictive performance of our hybrid model. This work will contribute to the understanding of the economic impact of SMEs. It will benefit a range of stakeholders, including policymakers, financial institutions, and other actors within this field. It may be of interest to future research to improve the usage of models by optimizing hyperparameters, utilizing new datasets, or exploring different types of dynamics in economics. While the proposed CNN–LSTM hybrid model has demonstrated superior performance in capturing both spatial and temporal dependencies, several limitations should be acknowledged. First, the increased architectural complexity results in higher computational cost and longer training times compared to traditional machine learning models, which may limit its applicability in resource-constrained environments. Second, the model's high capacity introduces a risk of overfitting, particularly when applied to small or imbalanced datasets, even when regularization and data augmentation techniques are employed. Third, the performance is sensitive to hyperparameter selection, requiring careful tuning to achieve optimal results. Future research could address these limitations by exploring model compression techniques, transfer learning from larger economic datasets, and advanced regularization methods to improve generalization.

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References

[1] F. Manzoor, L. Wei, and M. Siraj, "Small and medium-sized enterprises and economic growth in pakistan: An ardl bounds cointegration approach," *Heliyon*, vol. 7, no. 2, 2021.

[2] S. Benzidia and N. Makaoui, "Improving smes performance through supply chain flexibility and market agility: It orchestration perspective," *Supply Chain Forum: An International Journal*, vol. 21, no. 3, pp. 173–184, 2020.

[3] L. Westman, E. Moores, and S. L. Burch, "Bridging the governance divide: The role of smes in urban sustainability interventions," *Cities*, vol. 108, 2021.

[4] T. H. T. Thanh and V. N. Tron, "The differential effects of government support, inter-firm collaboration, and firm financial resources on sme performance in vietnam," *Cuadernos de Economía*, vol. 46, no. 130, pp. 124–134, 2023.

[5] H. Li, Y. Jiang, A. Ashiq, A. Salman, M. Haseeb, and M. S. Shabbir, "The role of technological innovation, strategy, firm's performance, and firm's size and their aggregate impact on organizational structure," *Managerial and Decision Economics*, vol. 44, no. 4, pp. 2010–2020, 2023.

[6] C. E. D. Marco, I. Martelli, and A. D. Minin, "European smes' engagement in open innovation: When the important thing is to win and not just to participate, what should innovation policy do?," *Technological Forecasting and Social Change*, vol. 152, 2020.

[7] M. Dabić, N. Stojčić, M. Simić, V. Potocan, M. Slavković, and Z. Nedelko, "Intellectual agility and innovation in micro and small businesses: The mediating role of entrepreneurial leadership," *Journal of Business Research*, vol. 123, pp. 683–695, 2021.

[8] A. Sircar, K. Yadav, K. Rayavarapu, N. Bist, and H. Oza, "Application of machine learning and artificial intelligence in oil and gas industry," *Petroleum Research*, vol. 6, no. 4, pp. 379–391, 2021.

[9] G. Lăzăroiu, M. Andronie, M. Iatagan, M. Geamănu, R. Ștefănescu, and I. Dijmărescu, "Deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms in the internet of manufacturing things," *ISPRS International Journal of Geo-Information*, vol. 11, no. 5, 2022.

[10] J. P. Bharadiya, "Leveraging machine learning for enhanced business intelligence," *International Journal of Computer Science and Technology*, vol. 7, no. 1, pp. 1–19, 2023.

[11] L. Crosato, C. Liberati, and M. Repetto, "Lost in a black-box? interpretable machine learning for assessing italian smes default," *Applied Stochastic Models in Business and Industry*, 2023.

[12] A. Angelopoulos, E. T. Michailidis, N. Nomikos, P. Trakadas, A. Hatziefremidis, S. Voliotis, and T. Zahariadis, "Tackling faults in the industry 4.0 era—a survey of machine-learning solutions and key aspects," *Sensors*, vol. 20, no. 1, 2019.

[13] M. Shehab, L. Abualigah, Q. Shambour, M. A. Abu-Hashem, M. K. Y. Shambour, A. I. Alsalibi, and A. H. Gandomi, "Machine learning in medical applications: A review of state-of-the-art methods," *Computers in Biology and Medicine*, vol. 145, 2022.

[14] O. Adeola, P. Gyimah, K. O. Appiah, and R. N. Lussier, "Can critical success factors of small businesses in emerging markets advance un sustainable development goals?," *World Journal of Entrepreneurship, Management and Sustainable Development*, vol. 17, no. 1, pp. 85–105, 2021.

[15] F. Liu, X. Zhou, J. Cao, Z. Wang, T. Wang, H. Wang, and Y. Zhang, "Anomaly detection in quasi-periodic time series based on automatic data segmentation and attentional lstm-cnn," *IEEE Transactions on Knowledge and Data Engineering*, vol. 34, no. 6, pp. 2626–2640, 2020.

[16] K. M. Rashid and J. Louis, "Times-series data augmentation and deep learning for construction equipment activity recognition," *Advanced Engineering Informatics*, vol. 42, 2019.

[17] Y. Luan and S. Lin, "Research on text classification based on cnn and lstm," in *2019 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)*, pp. 352–355, 2019.

[18] F. Aksan, V. Suresh, P. Janik, and T. Sikorski, "Load forecasting for the laser metal processing industry using vmd and hybrid deep learning models," *Energies*, vol. 16, no. 14, 2023.

[19] I. Afolabi, T. C. Ifunaya, F. G. Ojo, and C. Moses, "A model for business success prediction using machine learning algorithms," in *Journal of Physics: Conference Series*, vol. 1299, 2019.

[20] A. Belhadi, S. S. Kamble, V. Mani, I. Benkhati, and F. E. Touriki, "An ensemble machine learning approach for forecasting credit risk of agricultural smes' investments in agriculture 4.0 through supply chain finance," *Annals of Operations Research*, pp. 1–29, 2021.

[21] G. Kou, Y. Xu, Y. Peng, F. Shen, Y. Chen, K. Chang, and S. Kou, "Bankruptcy prediction for smes using transactional data and two-stage multi-objective feature selection," *Decision Support Systems*, vol. 140, 2021.

[22] S. Hamal and Ø. Senvar, "Comparing performances and effectiveness of machine learning classifiers in detecting financial accounting fraud for turkish smes," *International Journal of Computational Intelligence Systems*, vol. 14, no. 1, pp. 769–782, 2021.

[23] L. Wang, F. Jia, L. Chen, and Q. Xu, "Forecasting smes' credit risk in supply chain finance with a sampling strategy based on machine learning techniques," *Annals of Operations Research*, pp. 1–33, 2022.

[24] W. Zhang, S. Yan, J. Li, X. Tian, and T. Yoshida, "Credit risk prediction of smes in supply chain finance by fusing demographic and behavioral data," *Transportation Research Part E: Logistics and Transportation Review*, vol. 158, 2022.

[25] W. Zhang, G. Cui, Y. Wang, C. Zheng, and Q. Zhu, "A human comfort prediction method for indoor personnel based on time-series analysis," *Building Simulation*, vol. 16, no. 7, pp. 1187–1201, 2023.

[26] T. Zhu, C. Luo, Z. Zhang, J. Li, S. Ren, and Y. Zeng, "Minority oversampling for imbalanced time series classification," *Knowledge-Based Systems*, vol. 247, 2022.

[27] D. Maulud and A. M. Abdulazeez, "A review on linear regression comprehensive in machine learning," *Journal of Applied Science and Technology Trends*, vol. 1, no. 4, pp. 140–147, 2020.

[28] V. E. Sathishkumar, A. G. Ramu, and J. Cho, "Machine learning algorithms to predict the catalytic reduction performance of eco-toxic nitrophenols and azo dyes contaminants," *Alexandria Engineering Journal*, vol. 72, pp. 673–693, 2023.

[29] Z. Hu, Y. Zhao, and M. Khushi, "A survey of forex and stock price prediction using deep learning," *Applied System Innovation*, vol. 4, no. 1, 2021.

[30] C. H. Chen, K. Tanaka, M. Kotera, and K. Funatsu, "Comparison and improvement of the predictability and interpretability with ensemble learning models in qspr applications," *Journal of Cheminformatics*, vol. 12, pp. 1–16, 2020.

[31] N. J. Fai, W. K. Wey, K. Y. Qi, G. J. Xian, R. J. M. Chun, and Z. A. bin Abdul Salam, "Digits classification using random forest classifier," *Journal of Applied Technology and Innovation*, vol. 7, no. 3, 2023.

[32] Z. Amiri, A. Heidari, N. J. Navimipour, M. Unal, and A. Mousavi, "Adventures in data analysis: A systematic review of deep learning techniques for pattern recognition in cyber-physical-social systems," *Multimedia Tools and Applications*, pp. 1–65, 2023.

[33] Y. Liu, "Novel volatility forecasting using deep learning–long short term memory recurrent neural networks," *Expert Systems with Applications*, vol. 132, pp. 99–109, 2019.

[34] X. Yan, "Research on financial field integrating artificial intelligence: Application basis, case analysis, and svr model-based overnight," *Applied Artificial Intelligence*, vol. 37, no. 1, 2023.

[35] S. N. Khan, S. U. Khan, H. Aznaoui, C. B. Şahin, and Ö. B. Dinler, "Generalization of linear and non-linear support vector machine in multiple fields: a review," *Computer Science and Information Technologies*, vol. 4, no. 3, pp. 226–239, 2023.

[36] M. Ehtearm, H. G. Zadeh, A. Seifi, A. Fayazi, and M. Dehghani, "Predicting hydropower production using deep learning cnn-ann hybridized with gaussian process regression and salp algorithm," *Water Resources Management*, vol. 37, no. 9, pp. 3671–3697, 2023.

[37] B. Dou, Z. Zhu, E. Merkurjev, L. Ke, L. Chen, J. Jiang, and G. W. Wei, "Machine learning methods for small data challenges in molecular science," *Chemical Reviews*, vol. 123, no. 13, pp. 8736–8780, 2023.

[38] R. Wang, Q. Guo, S. Lu, and C. Zhang, "Tire defect detection using fully convolutional network," *IEEE Access*, vol. 7, pp. 43502–43510, 2019.

[39] Q. Zhang, N. Fragnito, X. Bao, and N. Sharma, "A deep learning method to predict ankle joint moment during walking at different speeds with ultrasound imaging: A framework for assistive devices control," *Wearable Technologies*, vol. 3, 2022.

[40] Y. He, P. Huang, W. Hong, Q. Luo, L. Li, and K. L. Tsui, "In-depth insights into the application of recurrent neural networks (rnns) in traffic prediction: A comprehensive review," *Algorithms*, vol. 17, no. 9, 2024.

[41] J. P. Bharadiya, "Exploring the use of recurrent neural networks for time series forecasting," *International Journal of Innovative Science and Research Technology*, vol. 8, no. 5, pp. 2023–2027, 2023.

[42] Y. Ren, D. Zhao, D. Luo, H. Ma, and P. Duan, "Global-local temporal convolutional network for traffic flow prediction," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 2, pp. 1578–1584, 2020.

[43] D. M. Belete and M. D. Huchaiah, "Grid search in hyperparameter optimization of machine learning models for prediction of hiv/aids test results," *International Journal of Computers and Applications*, vol. 44, no. 9, pp. 875–886, 2022.

[44] Y. W. Chen, Q. Song, and X. Hu, "Techniques for automated machine learning," *ACM SIGKDD Explorations Newsletter*, vol. 22, no. 2, pp. 35–50, 2021.