



Social ski driver conditional autoregressive-based deep learning classifier for flight delay prediction

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Abstract

The importance of robust flight delay prediction has recently increased in the air transportation industry. This industry seeks alternative methods and technologies for more robust flight delay prediction because of its significance for all stakeholders. The most affected are airlines that suffer from monetary and passenger loyalty losses. Several studies have attempted to analyse and solve flight delay prediction problems using machine learning methods. This research proposes a novel alternative method, namely social ski driver conditional autoregressive-based (SSDCA-based) deep learning. Our proposed method combines the Social Ski Driver algorithm with Conditional Autoregressive Value at Risk by Regression Quantiles. We consider the most relevant instances from the training dataset, which are the delayed flights. We applied data transformation to stabilise the data variance using Yeo-Johnson. We then perform the training and testing of our data using deep recurrent neural network (DRNN) and SSDCA-based algorithms. The SSDCA-based optimisation algorithm helped us choose the right network architecture with better accuracy and less error than the existing literature. The results of our proposed SSDCA-based method and existing benchmark methods were compared. The efficiency and computational time of our proposed method are compared against the existing benchmark methods. The SSDCA-based DRNN provides a more accurate flight delay prediction with 0.9361 and 0.9252 accuracy rates on both dataset-1 and dataset-2, respectively. To show the reliability of our method, we compared it with other meta-heuristic approaches. The result is that the SSDCA-based DRNN outperformed all existing benchmark methods tested in our experiment.

Keywords Deep long short-term memory · Deep recurrent neural network · Flight delay prediction · Social ski driver · Yeo-Johnson Transformation

1 Introduction

The civil aviation sector is a distributed network of large interconnected elements designed to meet the common aim of on-time air transportation and passengers expectations [1, 2]. Because of flight connectivity, flight delays at airports, especially for commercial hub airports, usually propagate to other individual airports or even to the entire air transportation network. Without proper monitoring and control, such delays can expand over time, resulting in poor airport performance and causing unnecessary dissatisfaction for passengers [1, 3]. Over the last few years, this sector has rapidly grown in areas such as customers, infrastructure and territorial coverage [4, 5]. A statistical report from the international air transport association (IATA) reveals that in 2012, airlines' worldwide base incurred over \$160 billion in total energy cost [6–8].

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With the rapid growth of Communication, Navigation and Surveillance (CNS), increased air traffic and airspace capacities, flight schedule planners try to reduce buffer time among flight departures and arrivals for maximising the utilisation of aircraft.

The air transportation network architecture is tight and complex, making it vital to develop accurate prediction models critical for intelligent aviation systems [9]. It is necessary to predict flight departure or arrival delays with high accuracy. Anxiety by the passengers can be avoided by efficiently arranging their schedules to have access to a prediction model for a specific airport taxi time, with an explanatory variable being computed before prediction [9–11]. Additionally, airport management aims to provide better service with improved airport gate availability [4, 12, 13]. Nowadays, an increase in air traffic and flight delays has become a severe and prominent issue globally [1]. Based on the United States (US) Bureau of Transportation Statistics (BTS) report, most airline flights arrived 15 min late at their destination [14–22], thus incurring a loss of \$30 billion, which is a challenge to the air transportation system [14, 23]. Delay analyses have become an important research topic, and delay prediction has been the subject of earlier studies [14, 24, 25]. As state earlier, delays have a significant financial impact. Therefore, it is important to introduce intelligent systems to automate airports, passengers, and commercial airlines' monitoring and decision processes [26]. Highly accurate predictions and real-time monitoring systems are indispensable tools to that effect [1, 9–11, 26–32]. Proposed strategies include collaborative decision making (CDM) [4, 33], ground delay programs (GDP) [4, 34], and air traffic flow management (ATFM) [4, 35] to improve the information flow among participating airports. A few years ago, the research methodologies utilised for predicting delay propagation were from statistical, network theory, machine learning and agent-enabled methods [4, 36].

Comparing statistical approaches with machine learning methods have become popular in recent years. The field of transportation systems and aerospace research has experienced a significant number of machine learning models such as K-nearest neighbour (k-NN), support vector machine (SVM) and artificial neural network (ANN) models [9]. Some studies seek to improve the model prediction performance by introducing variant neural network models [37–39]. Using only machine learning methods on historical data without an optimisation algorithm has proven ineffective. In contrast, our proposed method uses historical data from two datasets with a novel optimisation algorithm. The authors [14, 40] employed the traditional statistical approach to characterise and distribute flight delays. In [14, 41], the authors combine terminal airports weather forecasts, convective weather forecasts, and the

scheduled flights for predicting daily airport delay time in terms of the weather impacted traffic index (WITI) metric. As reported in the 2017 BTS report, only 0.72% of flight delays were attributed to extreme weather [14]. The most broadly used traffic prediction techniques are deep learning classifiers [42–45]. The deep learning techniques come under supervised and unsupervised machine learning algorithms [37–39, 42, 46–51]. None of the previous studies has taken multiple routes full account in the prediction. In contrast, we introduce a feature fusion method that utilises the complete flight information on different routes and combines them to improve the performance. In our studies, we will focus on non-weather-induced delays.

Our paper aims to propose a novel flight delay prediction strategy that utilises social ski driver conditional autoregressive-based (SSDCA-based) deep long short-term memory (LSTM). We conduct data pre-processing initially to improve the data quality; then, we perform the data transformation based on Yeo-Johnson transformation for further data processing. Yeo-Johnson transformation transfers the data with no loss of its original quality. It works like Box-cox transformation, but data values must not be strictly positive, and it is advantageous over other transformation techniques. Also, it makes the data distribution more symmetric, thereby handling any skewness from the datasets. We then perform feature fusion using the deep recurrent neural network (Deep RNN) for fusing the imperative features. Here, we train the Deep RNN by the developed SSDCA, which improves the model learning process. Finally, we perform flight delay prediction using the Deep LSTM. Furthermore, we compared the newly developed SSDCA with other optimisation algorithms such as social ski driver (SSD), particle swarm optimisation (PSO), ant colony optimisation (ACO), honey-bee optimisation (HBO) and earthworm optimisation algorithm (EWA) [52, 53]. The accuracy (AC) of the SSDCA outperforms the other existing methods. It is also worth mentioning that the proposed method's computational time is less than that of the other methods. In terms of error rate, such as root mean square error (RMSE), mean square error (MSE) and mean absolute error (MAE), the proposed SSDCA outperformed other methods.

The contribution of the paper is:

1.1 Proposed SSDCA enabled Deep LSTM for flight delay prediction

We introduced the classifier; SSDCA algorithm drove Deep LSTM by modifying the training process of the Deep LSTM with SSDCA algorithm newly proposed by incorporating SSD with CAViaR for biases and weights optimal tuning. We utilise the Deep RNN for feature fusion, which

is trained by the proposed SSDCA. Also, we adapted the SSDCA enabled Deep LSTM for predicting flight delays.

The rest of this paper is organised as follows: Sect. 2 describes the conventional flight delay prediction strategies employed in the literature and the challenges that inspire the development of the novel technique. Section 3 describes the proposed model for flight delay prediction based on the SSDCA-based deep learning classifier. Section 4 presents our model results and compares them with results from existing methods. Finally, Sect. 5 contains the results and discussion of the findings to conclude with possible future directions.

2 Related literature

The vast volume of collected data from the commercial aviation system makes developing machine learning and artificial intelligence algorithms a popular candidate approach in predicting flight delays. Traditional methods such as support vector machine, neural network, fuzzy logic, tree-based methods and K-nearest neighbour are the most common data-driven methods [2]. Güvercin et al. [48] proposed a clustered airport modelling approach for forecasting flight delays using airport networks. The method provided accurate forecasts for flight delays. However, during the training, the method uses only a few samples, which has an adverse effect on the model's prediction performance. Lambelho et al. [49] assessed airports generic strategic schedules using flight cancellation and delay predictions. The method's performance was good in cancellations and delayed flight departure but did not consider other features such as origin and destination to improve the predictions. Tu et al. [26] studied the factors causing major departure delays at Denver International Airport and the departure delay distribution using a probabilistic approach for United Airlines. The study attempts to separate contributing factors but focuses mainly on a single airport and does not consider the network effect. Pathomsiri et al. [50] assessed US joint production on-time and delay performance using a nonparametric function approach.

Some researchers apply operational research, simulation, queueing theory and optimisation to simulate flight delays for an optimised policymakers' system. Pyrgiotis et al. [4] studied an extensive network of delay propagation in major airports in the USA through network decomposition and an analytical queueing model. Ankan et al. [52] analyse delay propagation through air traffic networks with empirical data by developing a stochastic model. A Bayesian network method for estimating delay propagation considers the element-oriented and complex network distribution properties in three commercial aviation systems in the USA. These methods are valuable in

understanding interactions and root causes amongst delay occurrence elements. However, for the individual flights, these models did not yield sufficiently accurate predictions [53]. Rebollo et al. [54] predict departure delays by adopting random forest algorithms using air traffic characteristics as input features. When predicting departure delay for a two-hour forecast window, the model had an error of 21 min. Choi et al. [55] employ several machine learning algorithms and combine weather forecasts with flight schedules to predict scheduled times. Perez-Rodriguez et al. [56] proposed a model to predict daily aircraft delay probabilities in arrivals using asymmetric logic probability.

Recently, deep learning algorithms have been employed to improve the accuracy of flight delay prediction. Yu et al. [1] study flights at Beijing International Airport using a novel Deep Believe Network with support vector regression method (SVR) to analyse high-dimensional data. The model achieves a mean absolute error (MAE) of 8.41 min with high accuracy, but this study was limited to a single airport, and the propagation effects were not evaluated. Kim et al. [57] predict departure and arrival flight delays using a recurrent neural network (RNN) of an individual airport with a day-to-day sequence. Their study shows that a more in-depth architecture improved the accuracy of the RNN. However, the model can only perform a binary prediction of delay and does not quantify its magnitude. Chen and Li [15] developed a machine learning method for chained predictions of flight delays. The method provides an averagely reasonable, accurate and practical result for delay prediction but did not include an adequately big dataset which could have improved the accuracy. Ai et al. [33] developed Convolutional LSTM for temporal and spatial distribution flight delay prediction in the network. The method achieved good classification accuracy but did not include human factors.

Guleria et al. [5] presented a Multi-Agent Approach for reactionary flight delay prediction. The method helps in the flight scheduling system by identifying itineraries. However, the technique did not test delay propagation trees for better performance. Chen et al. [7] presented the Information Gain-Support Vector Machine method for determining how improvements in flight delays of the studied airlines based in China can reduce CO₂ emissions. The proposed approach reduces the limitations of the traditional data envelopment analysis (DEA) model. However, the authors focus on a limited number of airlines and recommend further experiments to confirm the method's validity. Maryam et al. [58] proposed a model for predicting flight delays based on the Levenberg–Marquart algorithm and deep learning. The accuracy of the proposed model in forecasting flight delays was good. However, the results show that the imbalanced form's standard deviation is

higher than all balanced evaluation parameters. Balanced data has more tendency to lead to a lower standard deviation (SD). Ehsan and Seyedmirsajad [59] proposed an approach to predict and analyse departure flight delays using the MATLAB R2018b [60] SVM implementations. The author recommended expanding the research to include National Aviation System (NAS)-wide airports in the analysis for more complete results. Daniel et al. [61] proposed predicting air traffic delays with multilevel input layers using a supervised neural network. The primary aim is to present a prediction model for delays in the air route by applying artificial neural networks (ANN) during the model training; authors concluded that parameters such as the day of the week, the block hour, or the airline had a higher influence than meteorology on the delay.

Regardless of the accuracy of the models, our observation on the methods used in the above works is that their training phase is slow, a characteristic that can become a limiting factor when the size of the data set grows. Another aspect of the training phase is the existence of outliers in the data. Such outliers could exist, for example, because of extreme delays that are not often encountered. Yu et al. [1] eliminate extreme value delays from the bottom and top 1% as outliers. Tu et al. [26] reduce the smoothing spline approach's influence by excluding extreme data preparation observations. The authors in [15] and [62] adopted a random forest method because of its low sensitivity to outliers. This average optimisation technique was unsuitable for our study because it may eliminate essential features through the manual selection process.

Accurate prediction of flight delay propagation at the national network level is essential, especially for flights with reoccurring delays, to reduce unwanted expenses. Based on the recent state-of-the-art architectural model of RNN units, LSTM has been promising in addressing this limitation. Researchers have applied it in several fields, including predicting traffic because the ability to learn time series features temporal correlation. Ma et al. [63] performed traffic speed prediction using LSTM on historical microwave detectors speed data and compared their approach with other approaches in terms of stability and accuracy. Liu et al. [64] proposed a generative deep learning model comprising LSTM encoder and decoder layers to predict aircraft trajectories. The LSTM shows that it can perform good feature extraction and learn useful temporal correlation features [65]. However, despite all these advancements, there is still a need to improve prediction performance and reliability, potentially using an optimisation algorithm to generate more efficient and accurate models.

2.1 Challenges

We elaborated on some issues faced by the existing predictive approaches for flight delay as follows:

- The deep learning model and convolutional LSTM [33] were developed for predicting flight delays. However, the method failed to consider the airport's delays to optimise take-off and landing intervals.
- In [49], the authors developed a generic strategic schedule assessment for predicting flight delays. However, the method does not utilise features such as unique air carriers, tail number of aircraft, and origin/destination airports with trigonometric transform function in the model training to enhance predictions' accuracy.
- In [1], the authors introduced a deep belief network method to determine flight delays; the method did not use an optimisation algorithm even without access to the required data on air traffic control because of confidentiality considerations for improving performance.

In our proposed method, we include the departure and arrival details in the selected features. Thus, our method overcomes the challenge of take-off and landing by considering the dataset's actual and scheduled time for both arrival and departure features. Our proposed method also uses features that include categorical and numerical data to enhance prediction performance.

3 Problem statement

Flight delays may occur because of several unforeseen events, which can affect airlines, airports and passengers. Developing more accurate models for predicting flight delays has become essential because of the rapid increase in flight complex data overflow, the limited number of prediction methods, and the air transportation system network's complexity. In this context, the proposed method builds an accurate flight delay prediction model. We assume the input data, represented by D , to be a collection of $D_{i,j}$'s, as defined in Eq. 1.

$$K = \{D_{i,j}\}; (1 \leq i \leq N'); (1 \leq j \leq T') \quad (1)$$

where N' is the total number of data points and T' is the total number of attributes. Hence, $D_{i,j}$ represents data in database K depicting j th mixed attribute of i th data. Thus, the expression $[N' \times T']$ denotes the size of the input data, indicated by $(D)_{N' \times T'}$. We will be extracting 6 features f_i from the input data D and fuse them into f as shown in Eq. 2 before feeding them as input to the deep learning classifier for predicting the flight delay as a final output O_f .

$$f = f_i; \quad i = 1 \text{ to } 6 \quad (2)$$

4 Flight delay prediction using the proposed social ski driver conditional autoregressive-based (SSDCA) deep learning classifier

This section explains the proposed SSDCA-based deep learning classifier for predicting flight delay. The steps followed in the developed model are pre-processing, data transformation, feature fusion, and prediction. We initially feed the pre-processing module with the input data and then perform data transformation using Yeo-Johnson transformation [66]. Afterwards, we forward the transformed data to the feature fusion module where Deep RNN performs the feature fusion [67]. We select an optimal number of layers in the Deep RNN method using the proposed SSDCA-based algorithm. The newly developed SSDCA algorithm combines the SSD [68] and CAViaR [69] algorithms. Finally, we perform the prediction using the Deep LSTM method [70] that we trained using the developed SSDCA method. Figure 1 shows the block diagram of the flight delay detection using the newly proposed SSDCA-based Deep learning.

4.1 Dataset description

The dataset used in this paper is from the US flight data downloaded from the US Government BTS for January and February of the year 2019 and 2020, respectively [71, 72]. The extracted data feature contains flight information with 21 features for time series analysis and flight delay

predictions, as shown in Table 1 [17]. There are over 1,000,000 row instances of commercial flights. The datasets records are inconsistent and incomplete, with many missing, duplicates and null values. We initially need to clean to make the data complete and suitable for further pre-processing by converting the attributes to the most appropriate forms for the application of deep learning and machine learning methods.

4.1.1 Features used for the model training and testing

Several features of the dataset are not relevant to our experiment, and we only kept the relevant features that have a high contribution to flight delay. We use the following features in training and testing our model:

- (i) *Flight Date*: The date on which the flight was performed.
- (ii) *Origin*: Departure airport.
- (iii) *Destination*: Arrival airport.
- (iv) *Departure delay*: The difference between actual departure time and scheduled departure time.
- (v) *Arrival delay*: The difference between actual arrival time and scheduled arrival time.
- (vi) *Distance*: The miles covered by the flight.

The departure and arrival delays are logically highly correlated, and any experience of delay on the departure flight will certainly affect the flight arrival. The authors in [24] have proved that the origin of congestion at the destination airport is, to a great extent, caused by the departure airport. For this reason, we have the selected features.

4.2 Pre-processing

The input data is a collection of categorical, numerical and time attributes. Categorical attributes indicate the airport station, for example, Heathrow, Delhi, Chennai etc. Numerical attributes represent the path values, humidity, etc. Finally, time attributes signify the date and time stamp for departure and arrival. Initially, we convert the categorical attributes to categorical numbers, meaning we assign the airport stations with a unique identifier number 1, 2, 3, etc. After that, we change both the numerical and time attributes from text to number data. Once we get the pre-processed data, we compute the missing value using the average and frequency method for numerical and categorical attributes. Thus, the pre-processed data output is indicated as in $(P)_{N \times T}$ where the dimension of pre-processed data is $[N \times T]$. Figure 2 shows the determination of pre-processed data output.

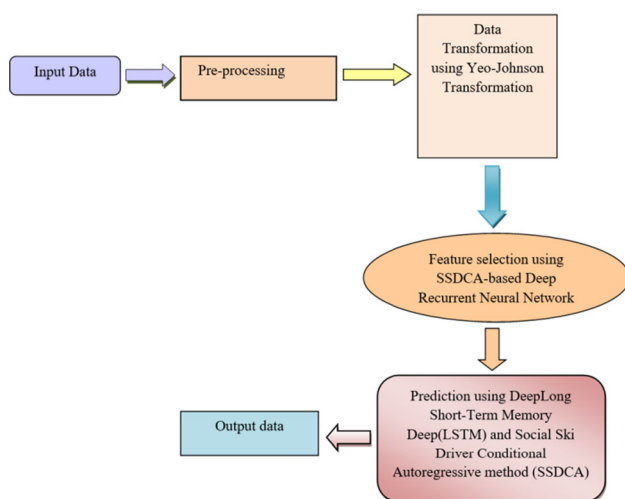
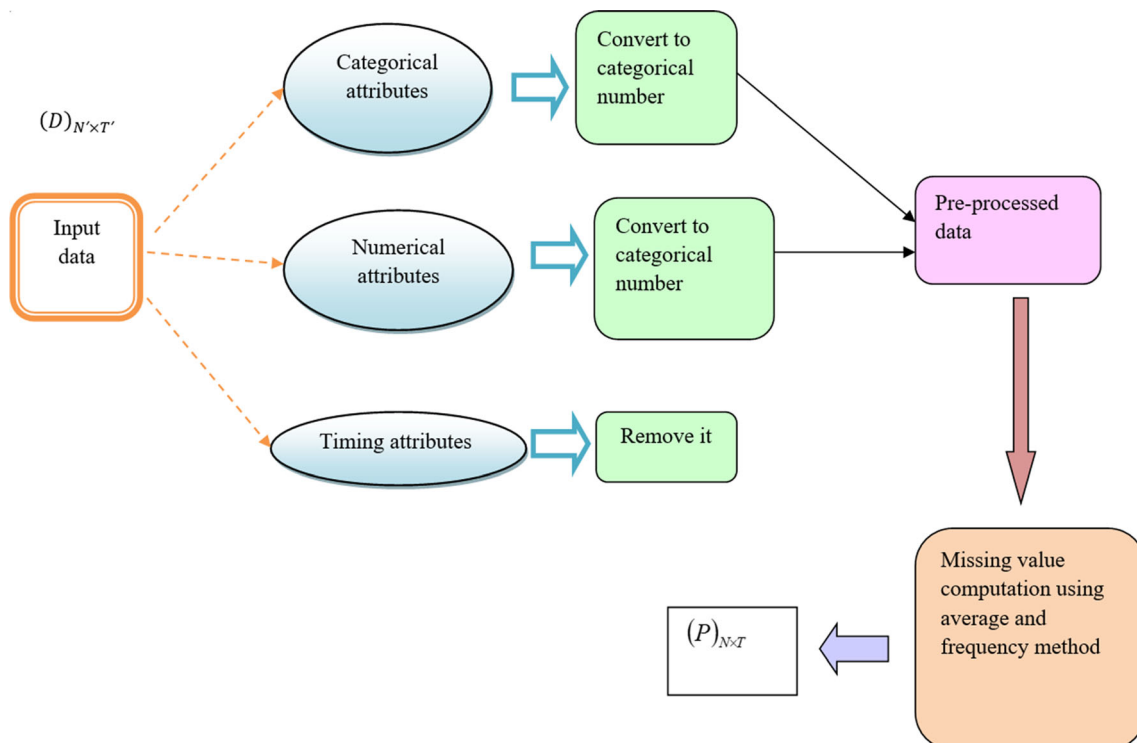


Fig. 1 Block diagram of the flight delay prediction using the proposed SSDCA-based Deep learning

Table 1 Datasets Information

S/No	Feature Name	Data Type	Attribute Type	Brief format explanation
1	Year	int64	Categorical	In four digits format, e.g. 2000
2	Month	int64	Categorical	In two digits format, e.g. 12
3	Day of month	int64	Categorical	In two digits format, e.g. 01–31
4	Day of week	int64	Categorical	In one-digit format, e.g. 1 (Monday)—7 (Sunday)
5	Departure time	float64	Continuous	In four digits format, e.g. 1456
6	Scheduled departure time	float64	Continuous	In four digits format, e.g. 1456
7	Arrival time	float64	Continuous	In four digits format, e.g. 1456
8	Scheduled arrival time	float64	Continuous	In four digits format, e.g. 1456
9	Unique carrier code	object	Categorical	2 letters code, e.g. PS
10	Flight number	object	Categorical	Number of flights, e.g. 1454
11	Actual elapsed time	float64	Continuous	In two digits format, e.g. 94
12	Scheduled elapsed Time	float64	Continuous	In two digits format, e.g. 94
13	Flight time	float64	Continuous	In two digits format, e.g. 94
14	Arrival time	float64	Continuous	In two digits format, e.g. 94
15	Departure time	float64	Continuous	In two digits format, e.g. 94
16	Origin	object	Categorical	3 letters code eg. LHR
17	Destination	object	Categorical	3 letters code, e.g. MAN
18	Distance	int64	Continuous	The miles covered, e.g. 448
19	Diverted	int64	Continuous	In two binary format, e.g. 0 or 1
20	Carrier delay	int64	Continuous	In two digits format, e.g. 94
21	Weather delay	int64	Continuous	In two digits format, e.g. 94

**Fig. 2** Schematic diagram for the determining-processing output

4.3 Data transformation using Yeo-Johnson transformation

We then pass the pre-processed data $(P)_{N \times T}$ to the data transformation phase, where the Yeo-Johnson transformation is used [66]. We find that the Yeo-Johnson transformation is better than other transformation methods because it produces well-organised data that is easier to use. Correctly formatted and transformed data improves the data quality and protects applications from potential landmines, such as null values, unexpected duplicates, incorrect indexing, and incompatible formats. Furthermore, the Yeo-Johnson transformation can make the data distribution more symmetric, and it does not require that the value be strictly positive. We estimate the parameters by applying this transformation to the response variable using the maximum penalised likelihood model. The Yeo-Johnson transformation expression is shown in Eq. 3.

$$J = \beta(\delta, M) = \begin{cases} \left(\frac{(M+1)^\delta - 1}{\delta} \right); & M \geq 0, \delta \neq 0 \\ \log(M+1); & M \geq 0, \delta = 0 \\ -\frac{((-M+1)^{2-\delta} - 1)}{(2-\delta)}; & M < 0, \delta \neq 2 \\ -\log(-M+1); & M < 0, \delta = 2 \end{cases} \quad (3)$$

where $J = \beta(\delta, M)$ is the output of the data transformation of R_j , δ is any real number of the power parameter in a piecewise function form that makes it continuous at the point of singularity ($\delta = 0$), where $\delta = 1$ is an identity transformation and M is the data vector with zero, negative and positive values or observations without restricting the type of observation needed stabilising the variance of the input datasets, which increase the features distribution symmetry and improving the validity of association measures (such as the correlation between features).

4.4 Feature fusion using proposed SSDCA-based deep RNN

Once the data transformation is performed, we then do the feature fusion based on the trained Deep RNN model of our SSDCA algorithm. In feature fusion, SSDs have greater throughput, continuous access times for quicker boot-ups, faster file transfers, and overall excellent performance. The CAViaR model specifies the evolution of the quantile over time using a special type of autoregressive process described in detail later. It applies to real data and can adapt to new risk environments. Thus, the SSDCA has the advantages of both SSD and CAViaR in feature fusion. After data transformation, the size of the data remains $N \times T$, hence for reducing the features, the feature fusion

step is fundamental in determining flight delays effectively. For example, the T attributes having six columns, meaning six features, as shown in the set $\{f_1, f_2, f_3, f_4, f_5, f_6\}$.

4.4.1 Correlation-based feature sorting

In this step, we perform the correlation for the six features. For example, we compute the correlation based on f_1 target values; thus, we get six correlation values. Then, we couple the features and change the columns based on high correlation values, and it precedes the feature fusion process for reducing the features. We applied spearman's rho correlation because our data has an ordinal level of measurement and follows a categorical distribution to measure the pairwise monotonicity of relationships by ranking from highest to lowest and choosing the high correlation values. Also, each of the variable change in one direction of category without necessarily at the same rate. It can be calculated as shown in Eq. 4.

$$C_s = 1 - \frac{6 \sum d_i^2}{(n^2 - n)} \quad (4)$$

where C_s is the rank between two features, d_i is the difference between two variable ranks for each data pair while $\sum d_i^2$ Represents the square sum difference between two features rank, and n is the number of instances.

4.4.2 Feature fusion and determination of β based on deep recurrent neural network

After feature fusion, we determine the β based on the Deep RNN classifier. Here, we take the features as the Deep RNN classifier's input for performing feature fusion using weights and bias-related with hidden layers.

4.4.2.1 Feature fusion Once we change the columns based on the correlation values, we perform the feature fusion based on Eq. 5.

$$f_k^{\text{fused}} = \sum_{i=1}^S \frac{\beta}{j} f_i \quad (5)$$

where $i = 1 + \frac{T}{l}$, $j = 1 \dots l$, T represents the total features and l refers to the number of selected features as shown in Eq. 6.

$$l = \frac{T}{S}; 1 \leq k \leq S \quad (6)$$

where the term k is the index of fused features and S is the last index of the fused features.

4.4.2.2 Structure of deep RNN This network architecture contains several recurrent hidden layers in the network hierarchy. However, the recurrent connection exists only among hidden layers. It takes the previous state output as the input to the next state and the iteration process with the hidden state information begins. The advantage of using a Deep RNN [67] classifier over state-of-art classifiers is that it operates effectively under changes of the input feature length. A recurrent feature associated with Deep RNN yields high performance in feature fusion accuracy and the required number of iterations. We used Deep RNN to find the best parameter values because it can process inputs of any length and approximate any function. We illustrate the structure of the Deep RNN classifier in Fig. 3.

The Deep RNN classifier defined the input vector of the layer f at time h as $U^{(f,h)} = \{U_1^{(f,h)}, U_2^{(f,h)}, \dots, U_r^{(f,h)}, \dots, U_n^{(f,h)}\}$, and the output vector of

the layer f at time h as $O^{(f,h)} = \{O_1^{(f,h)}, O_2^{(f,h)}, \dots, O_r^{(f,h)}, \dots, O_s^{(f,h)}\}$. The set of units for each element of output and input vectors n refers to the arbitrary unit number of layer f and v signifies total units. However, the total units of $(f-1)^{th}$ layer and the arbitrary unit number γ and ϕ . Here, the input propagation weight from $(f-1)^{th}$ layer to f^{th} layer is shown by $W^{(f)} \in I^{v \times \gamma}$, and f^{th} we denote recurrent layer weight as $w^{(f)} \in I^{v \times v}$, the term I signifies weight set. Therefore, the input vector components are as in Eq. 7.

$$U_n^{(f,h)} = \sum_{u=1}^{\gamma} z_{nu}^{(f)} O_z^{(f-1,h)} + \sum_{n'=1}^v \varepsilon_{nn'}^{(f)} O_{n'}^{(f,h-1)} \quad (7)$$

where, $z_{nu}^{(f)}$ and $\varepsilon_{nn'}^{(f)}$ refer to elements of $W^{(f)}$ and $w^{(f)}$, the term n' signifies the arbitrary unit number of f^{th} layer. Thus, the output vector of f^{th} the layer elements is as in Eq. 8.

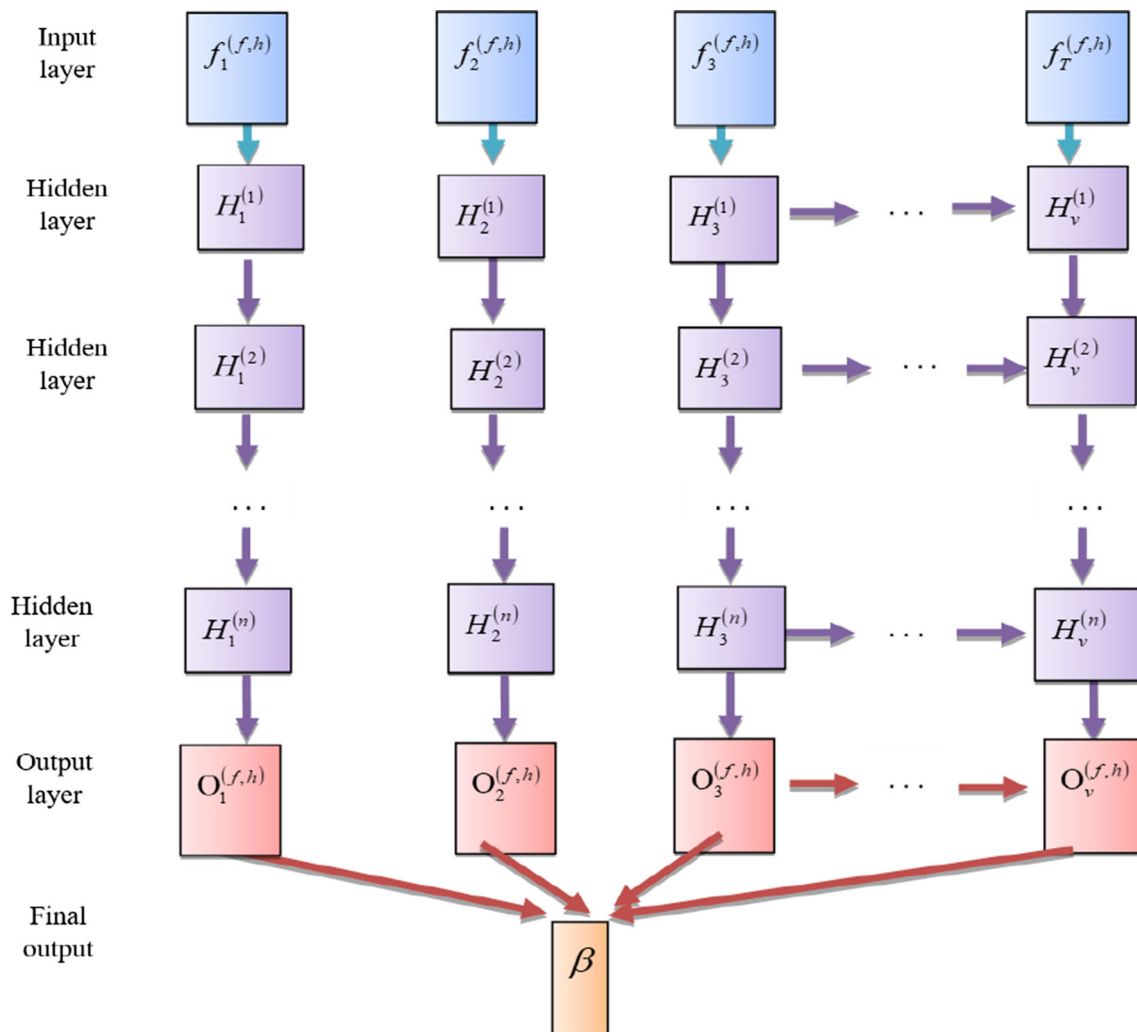


Fig. 3 Structure of Deep RNN

$$O_n^{(f,h)} = \mu^{(f)} \left(U_n^{(f,h)} \right) \quad (8)$$

where $\mu^{(f)}$ refers to the activation function. Thus, activation functions, like sigmoid function, are indicated by $\mu(U) = \tanh(U)$ rectified linear unit function (ReLU) is $\mu(U) = \max(U, 0)$, and we represent the logistic sigmoid function as $\mu(U) = \frac{1}{1+e^{-U}}$ are the employed activation function. To simplify the prediction process, consider ℓ^{th} weight as $z_{n\ell}^{(f)}$ and ℓ^{th} unit as $O_\ell^{(f-1,h)}$ and hence, we specified the bias as shown in Eq. 9.

$$O^{(f,h)} \text{ or } \beta = \mu^{(f)} \cdot \left(W^{(f)} O^{(f-1,h)} + w^{(f)} \cdot O^{(f,h-1)} \right) \quad (9)$$

Thus, the output of the classifier is indicated as $O^{(f,h)}$ or β . And $W^{(f)}$ is the input propagation weight, recurrent layer weight as $w^{(f)}$, unit as $O_\ell^{(f-1,h)}$ and $\mu^{(f)}$ refers to the activation function. The classifier is tuned by a proposed optimisation algorithm for updating the classifier's weights, enabling effective prediction performance.

4.4.2.3 Training data After the determination β , we computed the training data value by correlating the mean vector of data belonging to the class. The training data step is significant for the selected six features instance in model building to generate an output, as shown in Table 2.

We compute the training of the output β using Eq. 10.

$$\beta_{training}^{(i)} = \text{Correlation}(d_i, M_{d_i}) \quad (10)$$

where M_{d_i} refers to the mean vector of data d_i belonging to the class.

4.4.3 Training of deep recurrent neural network using social ski driver conditional autoregressive

We carried out the training process of Deep RNN [67] using the developed SSDCA technique for finding optimal weights to tune the Deep RNN [30] for feature fusion and flight delay prediction. The feature fusion based on the developed SSDCA categorises data by obtaining optimal weights and dealing with new data characteristics from distributed resources. The naturally

inspired SSD algorithm [68] has several evolutionary optimisation algorithms for reducing SVMs parameters and improving system performance. The goal of SSD is to search in space for near-optimal or optimal solutions. Thus, this approach is efficient in generating improved features for solving multi-aim optimisation problems. The method solves highly nonlinear problems with complicated constraints, can deal with heterogeneous data.

On the other hand, the CAViaR model [73] has received much attention to distributing direct returns to the quantile behaviour. We employ regression quantile to estimate and update the parameters. Tests of the model adequacy use a criterion independent of each probability period of all past information processes. The method also increased the convergence process and the diversity of solutions and improved the balance between exploitation and exploration. CAViaR models can adapt to new risk environments. Thus, integrating CAViaR with SSD is to enhance the overall algorithmic performance. We give the algorithmic steps of the proposed SSDCA as follows.

4.4.3.1 Initialisation The initial step of the SSDCA algorithm is the search agent's location initialisation, where the user determines the total number of agents. The agent's position is, as shown in Eq. 11.

$$X_v^t; \quad (1 \leq v \leq z) \quad (11)$$

where the term X_v^t refers to the agent's location at a time t , v is the velocity as and z is the total number of samples.

4.4.3.2 Objective function evaluation We select the optimal agent location using the minimal learning error as an optimal solution. We estimate the objective function error using Eqs. 12, 13, 14 and 15.

$$\text{MSE} = \frac{1}{Z} \sum_{h=1}^z (I_h - \beta_h)^2 \quad (12)$$

$$\text{RMSE} = \sqrt{\frac{1}{Z} \sum_{h=1}^z (I_h - \beta_h)^2} \quad (13)$$

$$\text{MAE} = \frac{1}{Z} \sum_{h=1}^z |I_h - \beta_h| \quad (14)$$

Table 2 Determination of training data

d_i/f_T	f_1	f_2	f_3	f_T	Target
d_1	$C(d_1, f_1)$	$C(d_1, f_2)$	$C(d_1, f_3)$	$C(d_1, f_T)$	$\beta_{training}$
d_2	$C(d_2, f_1)$	$C(d_2, f_2)$	$C(d_2, f_3)$	$C(d_2, f_T)$	$\beta_{training}$
d_3	$C(d_3, f_1)$	$C(d_3, f_2)$	$C(d_3, f_3)$	$C(d_3, f_T)$	$\beta_{training}$
d_4	$C(d_4, f_1)$	$C(d_4, f_2)$	$C(d_4, f_3)$	$C(d_4, f_T)$	$\beta_{training}$

$$AC = \frac{\text{TRUE POSITIVE} + \text{TRUE NEGATIVE}}{\text{TRUE POSITIVE} + \text{FALSE POSITIVE} + \text{TRUE NEGATIVE} + \text{FALSE NEGATIVE}} \quad (15)$$

where the classifiers estimated target, the output is I_h and β_h . The term z denotes the total number of samples.

4.4.3.3 Solution update using the SSDCA algorithm Once we compute the objective functions, the solution undergoes the location update based on SSDCA as shown in Eq. 16. The standard equation of the SSD velocity K_{lm}^{t+1} is given by Eq. 17.

$$X_{lm}^{t+1} = X_{lm}^t + K_{lm}^{t+1} \quad (16)$$

$$K_{lm}^{t+1} = \begin{cases} e \sin(m_1)(B_{lm}^t - X_{lm}^t) + \sin(m_1)(A_{lm}^t - X_{lm}^t); & s_2 \leq 0.5 \\ e \cos(m_1)(B_{lm}^t - X_{lm}^t) + \cos(m_1)(A_{lm}^t - X_{lm}^t); & s_2 > 0.5 \end{cases} \quad (17)$$

where K_{lm} signifies velocity of X_{lm} , and uniformly distributed random numbers represent m_1 and m_2 range between 0 to 1. B_{lm} refers to the optimal agent solution and A_{lm} denotes means a global solution for the entire population. Hence, Eq. (17) depicts the standard SSD equation that incorporates the CAViaR updated equation. Therefore, the CAViaR standard equation is given as in Eq. 18.

$$X_{lm}^t = \alpha_p + \sum_{h=1}^k \alpha_h X_{lm}(t-h) + \sum_{l=1}^r \alpha_l f(X_{lm}(t-h)) \quad (18)$$

Substituting $k = r = 2$ in Eq. 18 becomes Eq. 19.

$$X_{lm}^t = \alpha_0 + \alpha_1 X_{lm}(t-1) + \alpha_2 X_{lm}(t-2) + \alpha_1 f(X_{lm}(t-1)) + \alpha_2 f(X_{lm}(t-2)) \quad (19)$$

$$X_{lm}^{t+1} = X_{lm}^t + e \sin(m_1)(B_{lm}^t - X_{lm}^t) + \sin(m_1)(A_{lm}^t - X_{lm}^t) \quad (20)$$

Rearranging, Eq. 20, the solution becomes,

$$X_{lm}^{t+1} = X_{lm}^t [1 - e \sin(m_1) - \sin(m_1)] + e \sin(m_1) B_{lm}^t + \sin(m_1) A_{lm}^t \quad (21)$$

Substituting Eqs. 19 in 21 yields:

$$X_{lm}^{t+1} = \alpha_0 + \alpha_1 X_{lm}(t-1) + \alpha_2 X_{lm}(t-2) + \alpha_1 f(X_{lm}(t-1)) + \alpha_2 f(X_{lm}(t-2)) [1 - e \sin(m_1) - \sin(m_1)] + e \sin(m_1) B_{lm}^t + \sin(m_1) A_{lm}^t \quad (22)$$

Following the same procedure when considering case-2 in Eq. 17, which we refer to as Eq. 17b, we get:

$$K_{lm}^{t+1} = X_{lm}^t [e \cos(m_1) + \cos(m_1)] + e \cos(m_1) B_{lm}^t + \cos(m_1) * A_{lm}^t \quad (23)$$

Similarly, substituting Eqs. 19 in 23 results to:

$$X_{lm}^{t+1} = \alpha_0 + \alpha_1 X_{lm}(t-1) + \alpha_2 X_{lm}(t-2) + \alpha_1 f(X_{lm}(t-1)) + \alpha_2 f(X_{lm}(t-2)) [e \cos(m_1) + \cos(m_1)] + e \cos(m_1) B_{lm}^t + \cos(m_1) * A_{lm}^t \quad (24)$$

Thus, the final expression for the updated equation of the proposed SSDCA applied in performing the flight delay prediction is shown below in Eq. 25:

$$K_{lm}^{t+1} = \begin{cases} \alpha_0 + \alpha_1 X_{lm}(t-1) + \alpha_2 X_{lm}(t-2) + \alpha_1 f(X_{lm}(t-1)) + \alpha_2 f(X_{lm}(t-2)) \\ [1 - e \sin(m_1) - \sin(m_1)] + e \sin(m_1) B_{lm}^t + \sin(m_1) A_{lm}^t; & s_2 \leq 0.5 \\ \alpha_0 + \alpha_1 X_{lm}(t-1) + \alpha_2 X_{lm}(t-2) + \alpha_1 f(X_{lm}(t-1)) + \alpha_2 f(X_{lm}(t-2)) \\ [e \cos(m_1) + \cos(m_1)] + e \cos(m_1) B_{lm}^t + \cos(m_1) * A_{lm}^t; & s_2 > 0.5 \end{cases} \quad (25)$$

where $f(\cdot)$ denotes the fitness function considering the case-1 in Eq. 16, which we refer to as Eq. 16a.

Now substituting Eq. 17a in Eq. 16 results to:

4.4.3.4 Recheck the feasibility Once we test the updated position and each solution of the objective functions, we consider the optimal solution to be the one with maximal fitness.

4.3.3 Algorithm 1: Pseudocode of the SSDCA-based Deep RNN algorithm

```

1:  Input: Search agents location  $X_v^t; (1 \leq v \leq z)$ 
2:  Output: Optimal location
3:  Procedure:
4:  begin
5:      Agent's velocities and position are initialised (11)
6:      Consider fitness value should be minimal
7:      while stopping criteria are not met, do
8:          for whole agents do
9:              Compute fitness value based on equation (12)
10:             Sort agents based on fitness value
11:             Determine mean global solution and previous optimal solution
12:             Update the SSD equation using (17)
13:             Update the CAViaR equation using (18)
14:             Update the SSDCA equation based on (25)
15:          end for
16:      Check solution feasibility
17:      Return optimal solution
18:       $t = t + 1$ 
19:  end while
20:  The best solution is achieved
21: End

```

4.4.3.5 Termination The steps i to iv continue until we meet a specified maximum iteration number or achieve an optimal solution. The pseudocode of the developed SSDCA approach is shown in Algorithm 1.

We call F the output obtained from line 20 of algorithm 1.

4.4.4 Flight delay prediction based on proposed SSDCA-based deep LSTM

The feature fusion output F is plug into the Deep LSTM classifier [70] for predicting the flight delays training by the novel SSDCA, incorporating the SSD algorithm [68] and CAViaR [69]. We employ the Deep LSTM classifier because it takes less computational time to process the input time series data. Another significant benefit of Deep LSTM is that it requires less training data and can generate optimal results at a specific instance. This section presents an elaborate discussion of the Deep LSTM structure and framework utilised for optimising training weights.

4.5 Deep LSTM Architecture

We feed the Deep LSTM classifier with the fusion features F obtained from the feature fusion to accomplish the flight delay prediction. The Deep LSTM effectively achieves the

flight delay prediction by applying the classifier's memory cell, advantageous for the other classifiers. Here, the memory cell utilises the stored state information and acts as an accumulator. The Deep LSTM uses the input and their neighbours' past states to predict future states based on the convolutional operator and Hadamard product. We achieve an effective flight delay prediction using the high transitional kernel where the encoding and forecasting layers form the Deep LSTM structure. The forecasting network receives the initial input and outputs the cell encoding network. Also, the Deep LSTM uses a self-parametrised gate to clear cell access. The memory cell receives the state information if the gate gets activated when subject to the input. Whenever the forget gate is ON, the classifier forgets the past cell information. Because of insufficient decaying error backflow, information storage takes a long time over extended time intervals with a recurrent backpropagation. A significant advantage of the classifier is how it manages the information flow.

LSTM is an efficient and gradient-based method. The LSTM can bridge the minimal time lags learning to enforce constant error flow-through "constant error carousels" over 1000 discrete time steps within the particular unit. In terms of space and time, the LSTM is local. The LSTM algorithm can solve long-time lags of complex tasks that

other recurrent neural network algorithms cannot solve. Here, there is a convolutional architecture in the input to the state-to-state transition so that the forecasting problem solve has a structure in the LSTM. The classifier's rows and columns are the 3D tensors in spatial dimensions with inputs, hidden state and gates utilise. We define the input cell and states as vectors in spatial grid form to enhance the flight delay prediction performance. However, the classifier employs the previous state and neighbours' input cell to compute the future cell states. Thus, the Deep LSTM classifier includes an input $\{T_1, \dots, T_m\}$, hidden states $\{I_1, \dots, I_m\}$, cell output $\{D_1, \dots, D_m\}$, and gates x_m, y_m, z_m . Figure 4 describes the architecture of the Deep LSTM classifier.

Equation 26 defines the input gate output:

$$x_m = \gamma(S_x^T * T_m + S_x^I * I_{m-1} + S_x^D \circ D_{m-1} + \lambda^x) \quad (26)$$

where T_m is the input vector and S_x^T is the weight among the input layer and gate. The gate activation function is given by γ , and S_x^D is the weight vector between the cell input and output layer, and S_x^I is the weight between memory input and output layer, while I_{m-1} represents the previous cell output, and D_{m-1} is the previous memory unit output. The term λ^x represents input layer bias, and the character $*$ represents the Convolutional operator, and the character $\circ$ is the element-wise multiplication. Equation 27 represents the forget gate output:

$$y_m = \gamma(S_y^T * T_m + S_y^I * I_{m-1} + S_y^D \circ D_{m-1} + \lambda^y) \quad (27)$$

where S_y^T denotes weight among the input layer forget gate while the term S_y^I is the weight among the memory unit of

the previous layer and output gate and S_y^D is the weight among output gate and cells. The term λ^y represents the bias that relates to forgetting gates. Equation 28 represents the output generated from the output gate:

$$z_m = \gamma(S_z^T * T_m + S_z^I * I_{m-1} + S_z^D \circ D_{m-1} + \lambda^z) \quad (28)$$

where S_z^T represents the weight between the input layer and the output gate and S_z^I denotes the weight between the output gate and memory unit, and S_z^D denotes the weight between the output gate and the cell; the term λ^z is the output gate bias based on the activation function. Equation 29 represents the temporary cell state output.

$$\tilde{D}_m = \tanh(S_v^T * T_m + S_v^I * I_{m-1} + \lambda^v) \quad (29)$$

where λ^v represents the bias and S_v^T represents the weight between cell and input layer, while the symbol S_v^I represents the weight between cell and the memory unit. The cell output estimates adding the previous and current layer, temporary cell state and a memory unit. Equation 30 and Eq. 31 represent the cell output estimation.

$$D_\tau = y_m \circ D_{m-1} + x_m \circ \tilde{D}_\tau \quad (30)$$

$$D_m = y_m \circ D_{m-1} + x_m \circ \tanh(S_v^T * T_m + S_v^I * I_{m-1} + \lambda^v) \quad (31)$$

Equation 32 expresses the memory unit generated output:

$$I_m = z_m \circ \tanh(D_m) \quad (32)$$

where z_m represents the output gate, and the term I_m represents the block output memory. Thus, Eq. 33 represents the generated output O_m :

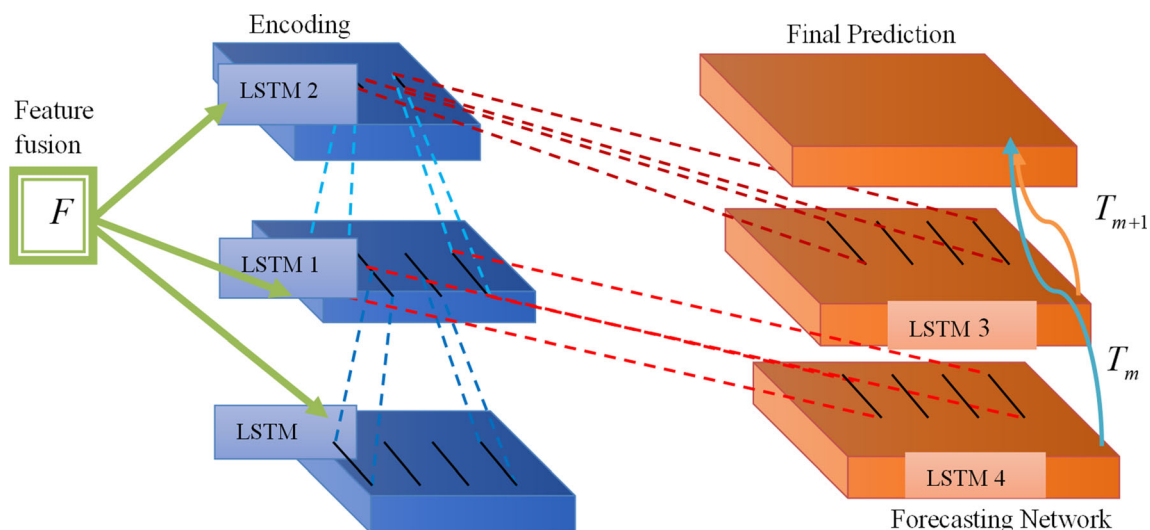


Fig. 4 Architecture of Deep LSTM classifier

$$O_m = \alpha (S_O^I \cdot I_m + \lambda^O) \quad (33)$$

where the output vector of weight among the memory unit is S_O^I and λ^O representing the output layer bias.

5 Results and discussion

This section describes the results of the proposed SSDCA-based Deep LSTM based on some benchmark metrics and compares our method with a set of methods from the literature. Table 3 presents the considered methods and the corresponding special names we give them.

5.1 Dataset source

The dataset considered for the experimentation is the flight delay prediction dataset with US flight data downloaded from the US Government Bureau of transportation statistics [71, 72].

5.1.1 January flight delay prediction dataset (dataset-1 [71])

This dataset contains the flights in January 2019 and January 2020. It contains over 400,000 flights, which translate into 400,000 rows. It contains 21 feature columns that specify the features of each flight. It includes destination airport, origin airport, departure time, arrival time, and aircraft information. We used the dataset for predicting flight delays at the destination airport for January.

5.1.2 February flight delay prediction dataset (dataset-2 [72])

This dataset contains the flights in February 2019 and February 2020. It contains over 400,000 flights, which translate into 400,000 rows. It contains 21 feature columns that specify the features of each flight. It includes

destination airport, origin airport, departure time, arrival time, and aircraft information. We used the dataset for predicting flight delays at the destination airport for February.

5.2 Evaluation metrics

We evaluate the proposed model performance using the MSE, RMSE, MAE and Accuracy metrics [17, 74–76].

5.2.1 MSE

This measures the average square difference between the estimated and target values, as shown in Eq. 10.

5.2.2 RMSE

This measures the square root of the average square difference between the actual and the predicted value, as shown in Eq. 11.

5.2.3 MAE

This measures the Mean of the absolute values of individual prediction errors over all instances in the test set, as shown in Eq. 12.

5.2.4 Accuracy

This measures the estimated value's closeness to a standard or actual value, as shown in Eq. 13.

5.3 Method comparisons

We analyse the developed model performance and compare it with the existing methods from the literature [1, 4, 6, 26] and other meta-heuristic approaches implemented with the Deep LSTM in our study.

5.3.1 Model evaluation

In this section, we compare the proposed SSDCA-based Deep LSTM by varying the percentage of the training and testing datasets to investigate the impact on the model's performance.

5.3.1.1 Analysis using dataset-1 Figure 9 in the appendix illustrates the analysis of the developed approach based on dataset-1 by considering the feature size as '6'. Figure 9a shows the analysis of RMSE regarding training data, with smaller values of RMSE being the favourable ones. When we consider 60% as training data, RMSE measured shows that our proposed method outperforms the existing

Table 3 Methods considered

S/No	Methods	Special name
1	Deep belief network (DBN)	Med 1
2	Gradient boosting classifier	Med 2
3	Information gain-SVM	Med 3
4	Multi-agent approach	Med 4
5	Deep LSTM	Med 5
6	PSO + Deep LSTM	Med 6
7	ACO + Deep LSTM	Med 7
8	SSD + Deep LSTM	Med 8
9	HBO + Deep LSTM	Med 9
10	EWA + Deep LSTM	Med 10

Table 4 Delay prediction using dataset-1

Method	DBN	Gradient boosting classifier	Information gain-SVM	Multi-agent approach	Deep LSTM	Proposed SSDCA-based deep LSTM
Number of flights delayed	5300	3337	2534	1365	1365	1640

methods, as shown in Table 9. For 90% training data, the developed model gained a minimum RMSE of 0.1114, whereas the remaining existing methods did not perform as well, with the actual values shown in Table 9.

Figure 9b shows the analysis of MSE in terms of training and testing data percentage. For 70% of training data, the MSE measured by the existing methods and our proposed method is shown in Table 9. For 90% training data, the developed model achieved a minimum MSE of 0.0134 compared to the other methods, with detailed values shown in Table 9.

Figure 9c shows the analysis of MAE in terms of training and testing data percentage. For 60% of training data, the MAE measured by our proposed method outperforms the other existing methods with a value of 0.1615. Detailed values are shown in Table 9. For 90% training data, the developed model achieved a minimum MAE of 0.0511 compared to the other methods, with detailed values shown in Table 9.

Figure 9d shows the analysis of Accuracy in terms of training and testing data percentage. For 70% of training data, the Accuracy measured by our proposed method outperforms the other existing methods with a value of 0.9156. Table 9 shows the detailed values of the other existing methods. For 90% training data, the developed model achieves an accuracy of 0.9362 compared to the other methods, with detailed values shown in Table 9.

5.3.1.2 Analysis using dataset-2 Figure 10 in the appendix illustrates the analysis of the developed approach based on dataset-2 by considering the feature size as ‘6’. Figure 10a shows the analysis of RMSE regarding training data, with smaller values of RMSE being the favourable ones. When we consider 60% as training data, RMSE measured shows that our proposed method outperforms the existing methods, as shown in Table 10. For 90% training data, the developed model gained a minimum RMSE of 0.1157, whereas the remaining existing methods did not perform as well, with the actual values shown in Table 10.

Figure 10b shows the analysis of MSE in terms of training and testing data percentage. For 70% of training data, the MSE measured by the existing methods and our proposed method is shown in Table 9. For 90% training data, the developed model achieved a minimum MSE of 0.0134 compared to the other methods, with detailed values shown in Table 10.

Figure 10c shows the analysis of MAE in terms of training and testing data percentage. For 60% of training data, the MAE measured by our proposed method outperforms the other existing methods with a value of 0.1701. Detailed values are shown in Table 9. For 90% training data, the developed model achieved a minimum MAE of 0.0557 compared to the other methods, with detailed values shown in Table 10.

Figure 10d shows the analysis of Accuracy in terms of training and testing data percentage. For 70% of training data, the Accuracy measured by our proposed method outperforms the other existing methods with a value of 0.9085. Table 10 shows the detailed values of the other existing methods. For 90% training data, the developed model achieves an accuracy of 0.9252 compared to the other methods, with detailed values shown in Table 10.

5.3.2 Delay prediction analysis

We now set the training data to be 70% of the dataset. Figure 5 represents the delay prediction gained using dataset-1. On January 15, 2020, the actual number of flights delayed was 1707, shown under the (original label). Our proposed method predicts 1640 and being the most accurate method. Detailed results of all methods appear in Table 4.

We now set the training data to be 70% of the dataset. Figure 6 represents the delay prediction gained using dataset-1. On February 20, 2020, the actual number of flights delayed was 2772, shown under the (original label). Our proposed method predicts 2874 and being the most accurate method. Detailed results of all methods appear in Table 5.

5.3.3 Convergence analysis

Figure 7 shows the analysis for convergence using dataset-1. For dataset-1, the MSE of the considered Deep LSTM method coupled with the different optimisers. PSO + Deep LSTM is 0.0132, ACO + Deep LSTM is 0.0130, SSD + Deep LSTM is 0.0130, HBO + Deep LSTM is 0.0128, and EWA + Deep LSTM the convergence is 0.0127. The MSE of the proposed SSDCA-based Deep LSTM is 0.0124. Hence, the proposed algorithm has the best convergence when compared to the other algorithms.

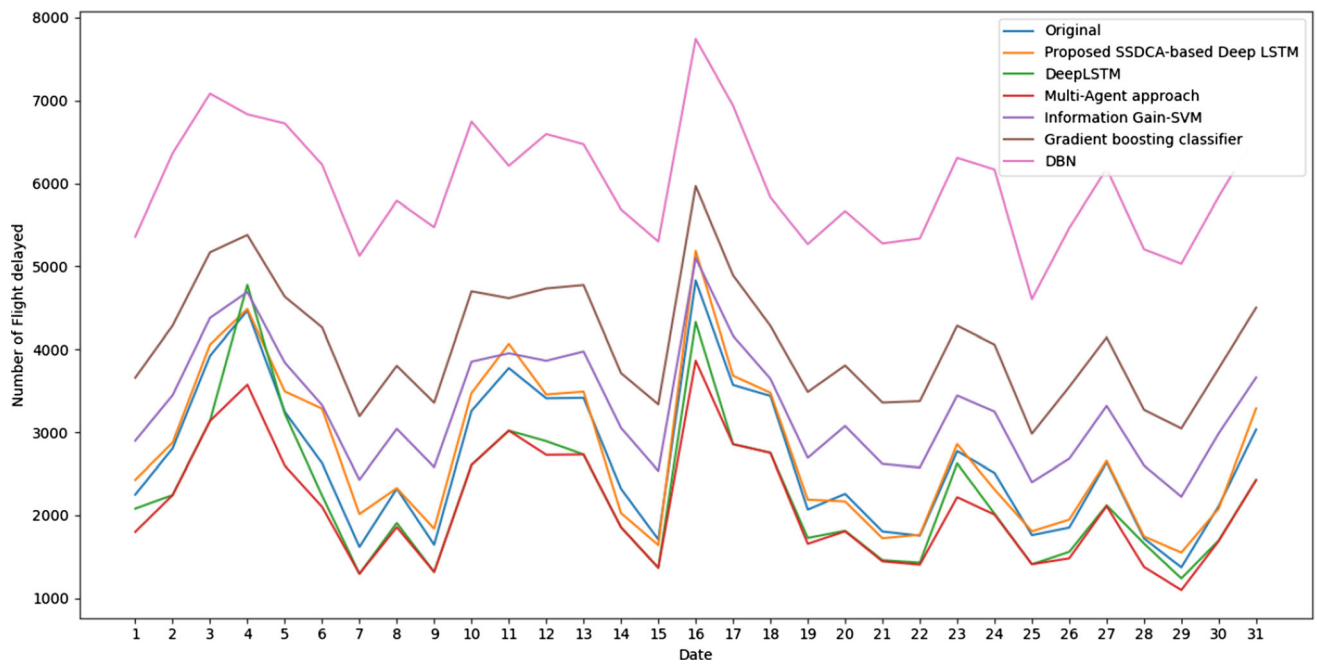


Fig. 5 Delay prediction using dataset-1

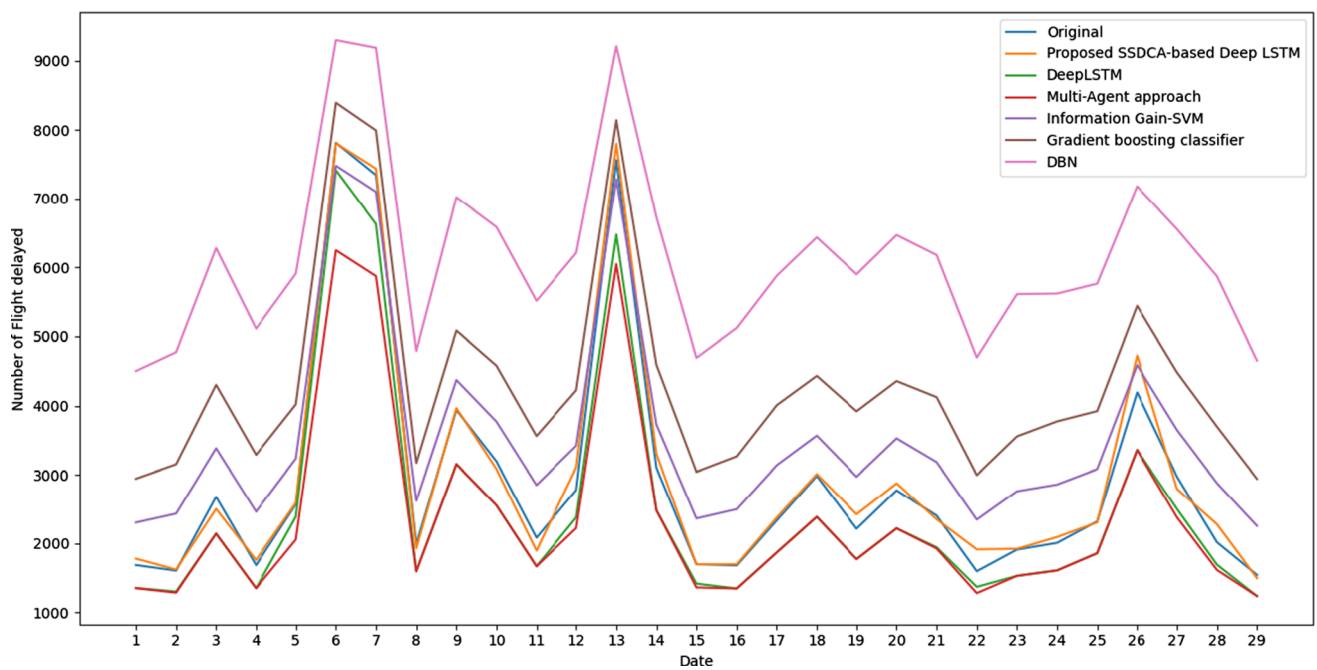


Fig. 6 Delay prediction using dataset-2

Table 5 Delay prediction using dataset-2

Method	DBN	Gradient boosting classifier	Information gain-SVM	Multi-agent approach	Deep LSTM	Proposed SSDCA-based deep LSTM
Number of flights delayed	6472	4357	3525	2217	2217	2874

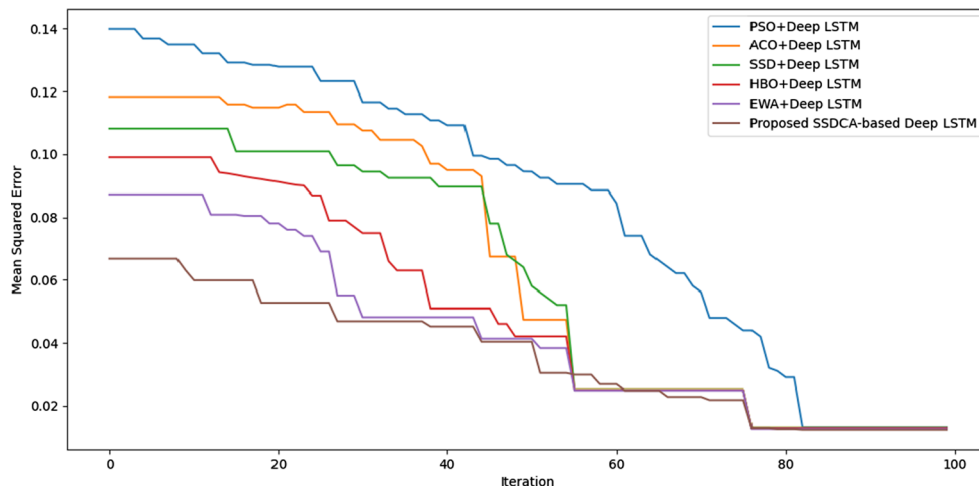


Fig. 7 Convergence analysis using dataset-1

Figure 8 shows the analysis of convergence using dataset-2. For dataset-2, the MSE of the considered Deep LSTM method coupled with the different optimisers. PSO + Deep LSTM is 0.0157, ACO + Deep LSTM is 0.0148, SSD + Deep LSTM is 0.0136, HBO + Deep LSTM is 0.0130, and the convergence of EWA + Deep LSTM is 0.0119, and for the Proposed SSDCA-based Deep LSTM the convergence is 0.0108. Hence, the proposed algorithm has the best convergence when compared to the other algorithms.

5.4 Comparative discussion

Table 6 illustrates the comparative results of the proposed SSDCA-based Deep LSTM approach. When considering the feature size as '6' for dataset-1 our proposed approach gained minimum RMSE and MSE values. The RMSE measured by the proposed SSDCA-based Deep LSTM is

0.1114. In contrast, the existing DBN, gradient boosting classifier, information gain-SVM, multi-agent approach, and Deep LSTM achieved the RMSE of 0.2953, 0.2229, 0.1878, 0.1165, and 0.1154, respectively. The MSE achieved by the existing DBN, gradient boosting classifier, information gain-SVM, multi-agent approach, Deep LSTM, and proposed SSDCA-based Deep LSTM for feature size '6' is 0.0872, 0.0497, 0.0353, 0.0136, 0.0133, and 0.0124 respectively. Table 3 shows that the proposed approach achieved minimal RMSE and MSE of 0.1065 and 0.0113 with dataset-2. The existing DBN, gradient boosting classifier, information gain-SVM, multi-agent approach, and Deep LSTM achieved the RMSE of 0.2971, 0.2240, 0.1892, 0.121, 0.1143 and 0.1065, respectively. The MSE achieved by the existing DBN, gradient boosting classifier, information gain-SVM, multi-agent approach, Deep LSTM, and proposed SSDCA-based Deep LSTM for

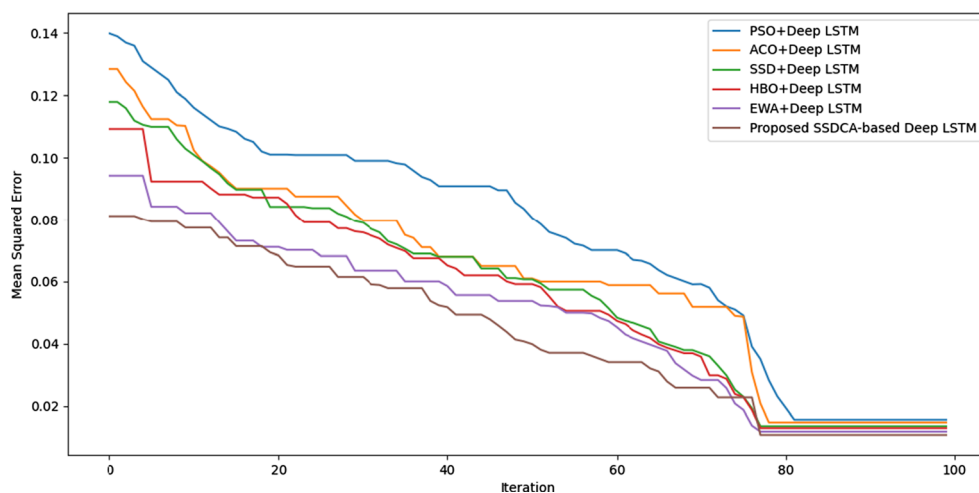


Fig. 8 Convergence analysis using dataset-2

Table 6 Comparative discussion

Dataset	Metrics	DBN	Gradient boosting classifier	Information gain-SVM	Multi-agent approach	Deep LSTM	Proposed SSDCA-based deep LSTM
Dataset 1	RMSE	0.2953	0.2229	0.1878	0.1165	0.1154	0.1114
	MSE	0.0872	0.0497	0.0353	0.0136	0.0133	0.0124
Dataset 2	RMSE	0.2971	0.2240	0.1892	0.1215	0.1143	0.1065
	MSE	0.0883	0.0502	0.0358	0.0148	0.0131	0.0113

feature size '6' is 0.0883, 0.0502, 0.0358, 0.0148, 0.0131 and 0.0113 respectively.

From our analysis, we show that our proposed method offers higher accuracy and needs fewer iterations than the existing methods. Also, it is more versatile in terms of skewness. CAViaR models can adapt to new risk environments, and LSTMs avoid the long-term dependency problem. RNN can process inputs of any length, and RNN with a deep network can approximate any function. Deep RNN can be much more efficient in terms of computation and the number of parameters.

5.5 Statistical analysis

Table 7 shows the statistical analysis. In the statistical analysis, the proposed method's RMSE and MSE Mean is 0.1113, 0.0124, and the variance is 0.0002 using dataset-1. Conducting the same statistical analysis using dataset-2, the mean and variance of the proposed method were 0.1063, 0.0111 and 0.0002. The proposed method has a

minimum variance than the other existing methods for both RMSE and MSE.

5.6 Computational time analysis

We perform our experiment on a Personal Computer (PC) with Intel(R) Core(TM) i7-9700 CPU with a processor speed of 3.00 GHz and 32 GB RAM. We used libraries such as TensorFlow Core-2.4.1, TensorFlow GPU-2.4.1, NumPy-1.19.1, pandas-0.25.3, sci-kit learn-0.23.2, Scipy-1.5.2, PySimpleGUI-4.29.0 and Matplotlib-3.3.1. Table 8 shows the computational wall time. The computational time analysis shows that our proposed SSDCA-based Deep LSTM needs 300 s and outperforms all other methods. Table 8 shows detail computational time requirements (Table 8).

Table 7 Statistical analysis

Dataset	Metrics	DBN	Gradient boosting classifier	Information gain-SVM	Multi-agent approach	Deep LSTM	Proposed SSDCA-based deep LSTM
Dataset-1	RMSE	0.2953	0.2229	0.1878	0.1165	0.1154	0.1115
	Mean	0.2947	0.2225	0.1872	0.1162	0.1150	0.1113
	Variance	0.0006	0.0004	0.0006	0.0003	0.0004	0.0002
	MSE	0.0872	0.0497	0.0353	0.0136	0.0133	0.0124
	Mean	0.0868	0.0490	0.0350	0.0131	0.0130	0.0122
	Variance	0.0004	0.0007	0.0003	0.0005	0.0003	0.0002
Dataset-2	RMSE	0.2971	0.2240	0.1892	0.1215	0.1143	0.1065
	Mean	0.2965	0.2236	0.1885	0.1210	0.1139	0.1063
	Variance	0.0006	0.0004	0.0007	0.0005	0.0004	0.0002
	MSE	0.0883	0.0502	0.0358	0.0148	0.0131	0.0113
	Mean	0.0878	0.0498	0.0353	0.0144	0.0126	0.0111
	Variance	0.0005	0.0004	0.0005	0.0004	0.0005	0.0002

Table 8 Computational time

Methods	Computational time (sec)
DBN	660.00
Gradient boosting classifier	690.00
Information gain-SVM	480.00
Multi-agent approach	630.00
Deep LSTM	420.00
Proposed SSDCA-based Deep LSTM	300.00

6 Conclusions and future work

Many factors can cause flight delays, ranging from failure in processes to late departure or aircraft arrival. The reasons for flight delay generate an enormous, complex amount of data used by machine learning methods to make crucial decisions because of the importance of flights arriving or departing on-time for the airport, airlines and passengers. Developing flight delay prediction models with high accuracy is necessary. In this paper, we propose a novel optimised forecasting model with Deep LSTM for flight delay prediction. We utilise the developed SSDCA to train the Deep LSTM and the Deep RNN for fusing the features. The newly proposed SSDCA works by combining SSD and CAViaR algorithms. We employ the novel SSDCA to identify the best weights for effective flight delay prediction using the US Government Bureau of transportation statistics dataset.

Initially, we perform the pre-processing from the input data and then the data transformation based on the Yeo-Johnson transformation. Afterwards, we perform the feature fusion using the Deep RNN to extract the useful features from the original datasets containing complex and nonlinear structures with spatial and temporal correlations. We introduced a two-step training procedure to help integrate the fused features and prediction layer of the model. Finally, we apply the Deep LSTM for flight delay prediction. Here, we use an advanced optimisation method named SSDCA to train the Deep LSTM and Deep RNN. We evaluate our proposed SSDCA-based Deep LSTM and

compare it with four benchmark methods: DBN, gradient boosting classifier, information gain-SVM, multi-agent approach, and Deep LSTM, including other developed meta-heuristic approaches PSO + Deep LSTM, ACO + Deep LSTM, SSD + Deep LSTM, HBO + Deep LSTM and EWA + Deep LSTM. Our approach had a minimal RMSE and MSE of 0.1115 and 0.0124 on dataset-1, with 0.1065 and 0.0113 on dataset-2. The novel SSDCA enabled approach performance has shown superior accuracy with a higher convergence rate than the other five meta-heuristic approaches regarding model accuracy and convergence analysis.

The results we get from our approach are promising. It illustrates how we can improve predicting flight delays using deep learning techniques with optimisation algorithms to inform departing and arriving policies and better airport facilities management. At the same time, the stakeholders can attain efficient and improve passenger satisfaction. The study can be extended further. One direction could be to consider more attributes. While there is no perfect delay prediction, in the future, we plan to investigate further flights with significant delay even though they are rare events. At the same time, we keep the error range on a regular flight with a minimally acceptable level so that departing and arriving policies are developed with less complexity. Secondly, to investigate the performance, we will test our proposed technique on other data sets or other sampling data from different sectors, such as maritime or rail. Finally, we will explore advanced optimisation approaches to improve the proposed method's performance towards a data-driven departure and arrival planning strategy, supporting airports, airlines and passengers to plan travel.

Appendix

Plots showing the performance results of the methods from Tables 9 and 10.

See Figs. 9 and 10

Table 9 Results comparison of our proposed method with other existing methods across different evaluation metrics on dataset-1

S/ No	Training/ testing (%)	Method/metrics	Med 1	Med 2	Med 3	Med 4	Med 5	Med 6	Med 7	Med 8	Med 9	Med 10	Proposed SSDCA-based deep LSTM
1	60/40	RMSE	0.5891	0.4471	0.3775	0.2473	0.2328	0.2280	0.2261	0.2258	0.2258	0.2243	0.2235
		MSE	0.3471	0.1999	0.1425	0.0611	0.0542	0.0519	0.0511	0.0511	0.0509	0.0503	0.0499
		MAE	0.5291	0.3971	0.3175	0.1989	0.1845	0.1756	0.1674	0.1645	0.1632	0.1625	0.1614
		Accuracy	0.7528	0.7656	0.7857	0.7924	0.8067	0.8156	0.8237	0.8398	0.8478	0.8756	0.9013
2	70/30	RMSE	0.5213	0.3874	0.3259	0.2078	0.2016	0.1963	0.1955	0.1950	0.1947	0.1946	0.1931
		MSE	0.2615	0.1501	0.1062	0.0432	0.0406	0.0385	0.0382	0.0380	0.0379	0.0378	0.0373
		MAE	0.4567	0.3367	0.2656	0.1573	0.1515	0.1485	0.1454	0.1450	0.1444	0.1436	0.1375
		Accuracy	0.7598	0.7720	0.7896	0.7995	0.8123	0.8195	0.8285	0.8425	0.8534	0.8798	0.9156
3	80/20	RMSE	0.4174	0.3154	0.2664	0.1682	0.1646	0.1588	0.1584	0.1582	0.1580	0.1577	0.1576
		MSE	0.1742	0.0995	0.0710	0.0283	0.0271	0.0252	0.0251	0.250	0.0249	0.0249	0.0248
		MAE	0.3567	0.2667	0.2056	0.1178	0.1134	0.1076	0.1066	0.1056	0.1020	0.1010	0.1010
		Accuracy	0.7754	0.7845	0.7945	0.8045	0.8196	0.8295	0.8367	0.8543	0.8634	0.8956	0.9268
4	90/10	RMSE	0.2952	0.2228	0.1878	0.1164	0.1154	0.1148	0.1140	0.1138	0.1133	0.1126	0.1114
		MSE	0.0871	0.0496	0.0352	0.1356	0.0133	0.0131	0.0130	0.0129	0.0128	0.0126	0.1024
		MAE	0.2487	0.1674	0.1267	0.0616	0.0594	0.0585	0.0580	0.0572	0.0572	0.0567	0.0511
		Accuracy	0.8034	0.8278	0.8584	0.8645	0.8756	0.8834	0.8907	0.9056	0.9156	0.9265	0.9361

Table 10 Results comparison of our proposed method with other existing methods across different evaluation metrics on dataset-2

S/ No	Training/ testing (%)	Method/metrics	Med 1	Med 2	Med 3	Med 4	Med 5	Med 6	Med 7	Med 8	Med 9	Med 10	Proposed SSDCA-based deep LSTM
1	60/40	RMSE	0.5904	0.4474	0.3786	0.2478	0.2428	0.2408	0.2397	0.2382	0.2350	0.2338	0.2302
		MSE	0.386	0.2001	0.1433	0.0614	0.0589	0.0580	0.0574	0.0567	0.0552	0.0546	0.0530
		MAE	0.5315	0.3956	0.3267	0.1967	0.1915	0.1895	0.1825	0.1795	0.1750	0.1732	0.1701
		Accuracy	0.7598	0.7756	0.7834	0.7956	0.8052	0.8167	0.8256	0.8367	0.8578	0.8626	0.8942
2	70/30	RMSE	0.5126	0.3869	0.3280	0.2103	0.2091	0.2076	0.2073	0.2058	0.2046	0.2016	0.1984
		MSE	0.2628	0.1497	0.1076	0.0442	0.0437	0.0431	0.0429	0.0423	0.0418	0.0406	0.0393
		MAE	0.4626	0.3367	0.2756	0.1576	0.1491	0.1476	0.1467	0.1445	0.1427	0.1406	0.1375
		Accuracy	0.7645	0.7834	0.7945	0.8013	0.8146	0.8245	0.8356	0.8467	0.8596	0.8694	0.9085
3	80/20	RMSE	0.4183	0.3159	0.2681	0.1717	0.1703	0.1702	0.1701	0.1696	0.1687	0.1680	0.1675
		MSE	0.1750	0.0998	0.0178	0.0294	0.0290	0.0290	0.0289	0.0287	0.0284	0.0282	0.0280
		MAE	0.3567	0.2658	0.2181	0.1217	0.1203	0.1202	0.1201	0.1196	0.1187	0.1180	0.1175
		Accuracy	0.7756	0.7956	0.8056	0.8145	0.8256	0.8352	0.8426	0.8567	0.8631	0.8745	0.9156
4	90/10	RMSE	0.2968	0.2238	0.1888	0.1214	0.1200	0.1198	0.1183	0.1181	0.1174	0.1165	0.1157
		MSE	0.0881	0.0500	0.0356	0.0147	0.0144	0.0143	0.0140	0.0139	0.0137	0.0135	0.0134
		MAE	0.2368	0.2238	0.1388	0.0614	0.0600	0.0593	0.0583	0.0581	0.0573	0.0565	0.0557
		Accuracy	0.7967	0.8042	0.8152	0.8221	0.8372	0.8442	0.8517	0.8615	0.8742	0.9042	0.9252

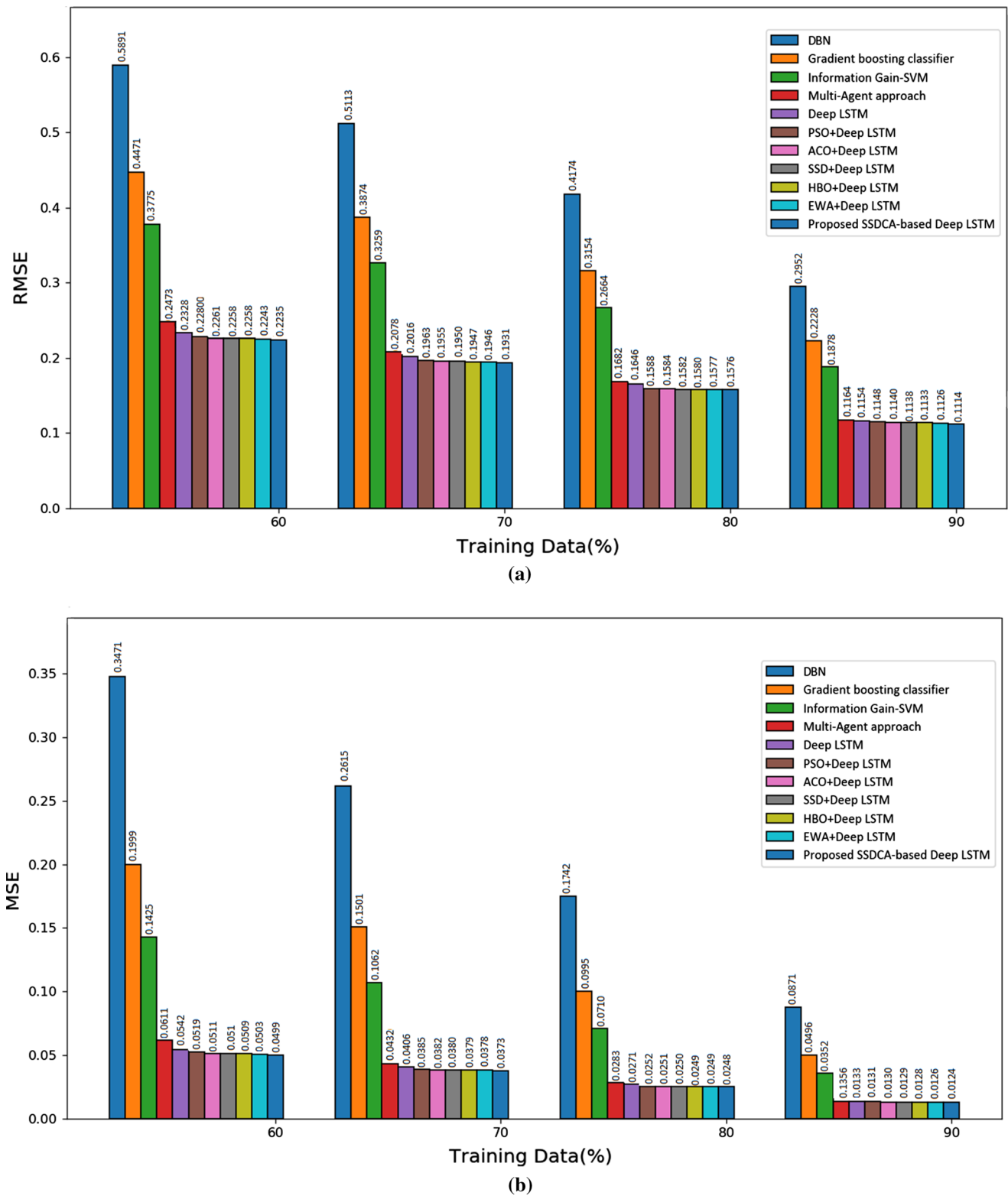


Fig. 9 Analysis using dataset-1 with feature size 6, **a** RMSE, **b** MSE, **c** MAE, **d** Accuracy

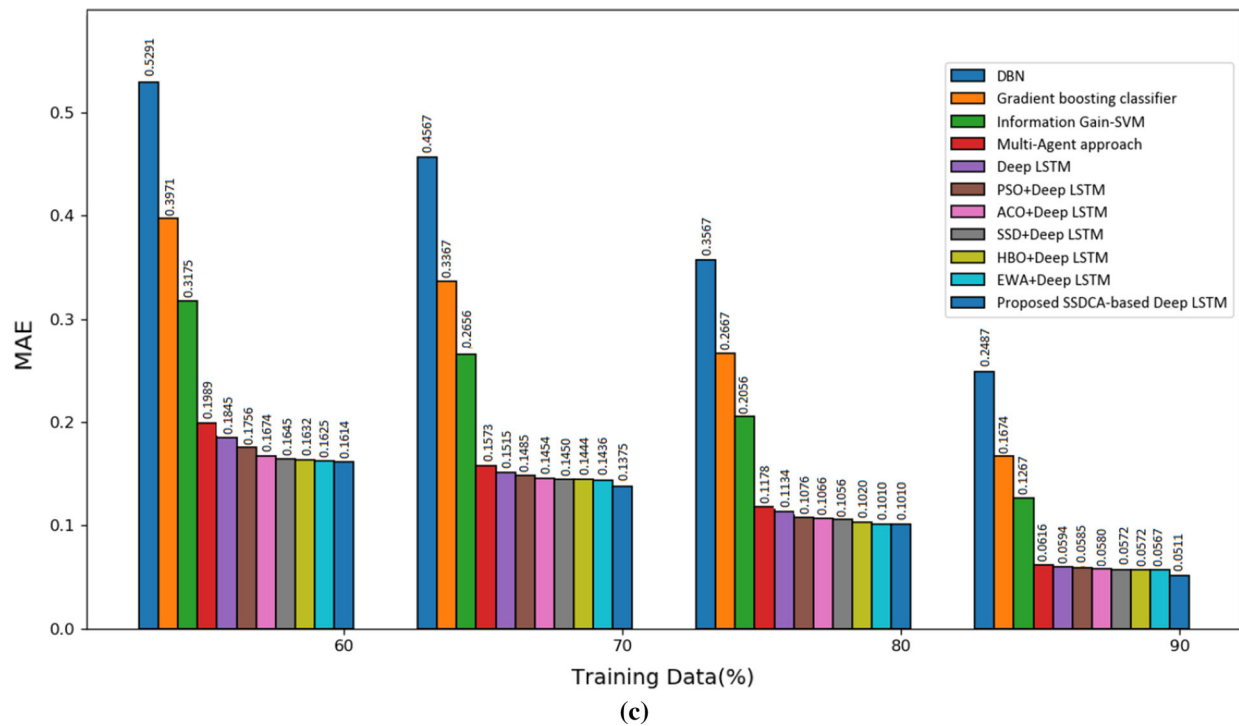
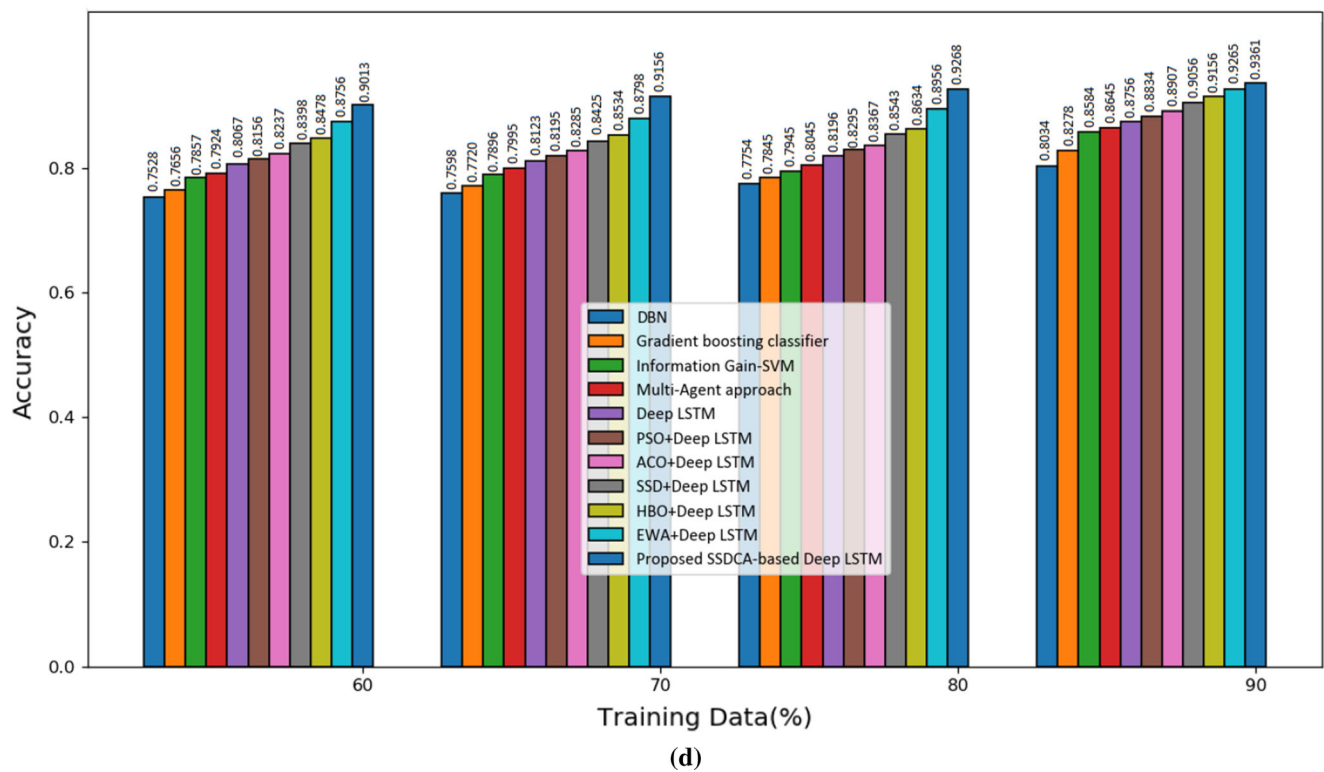


Fig. 9 continued

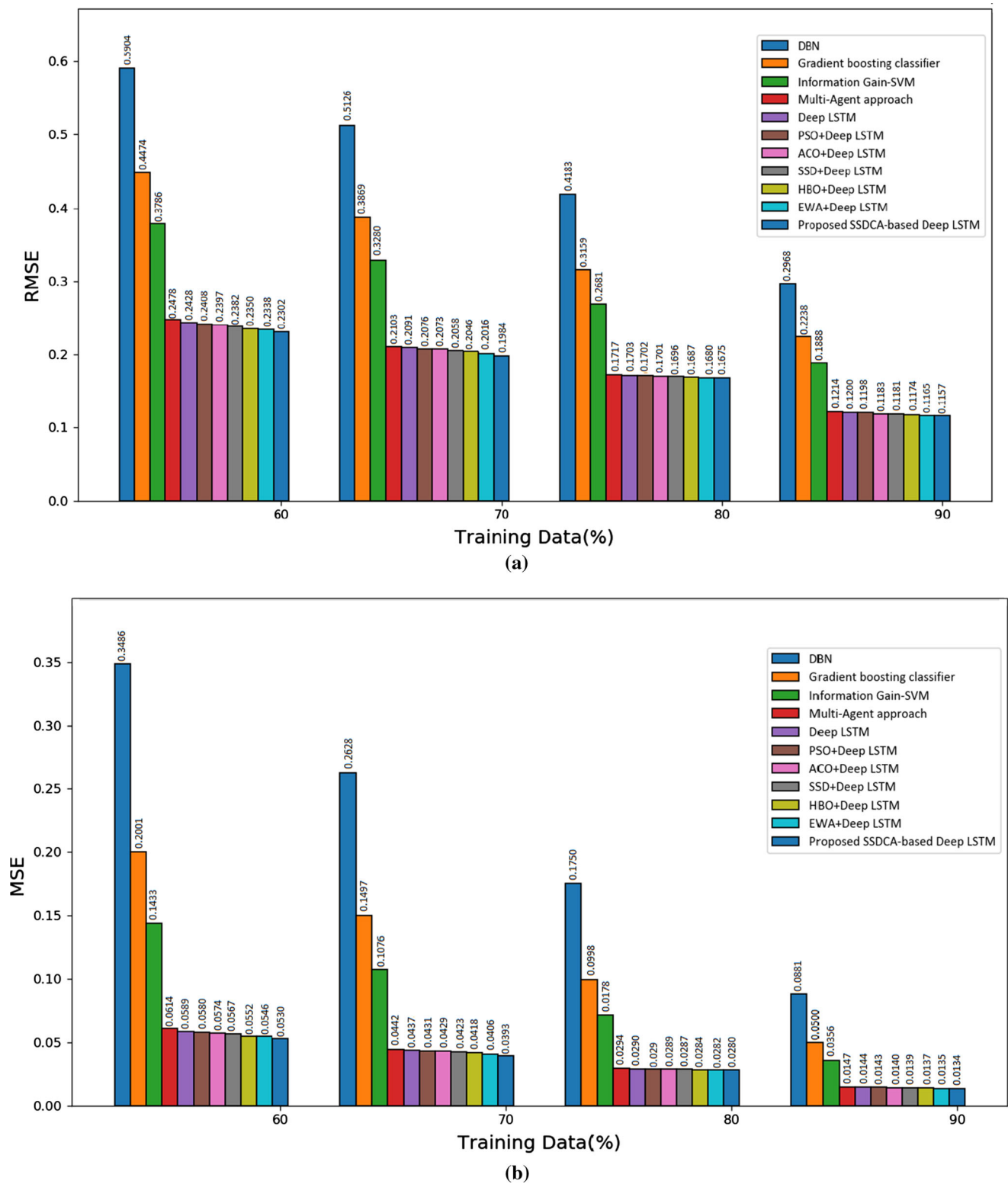


Fig. 10 Analysis using dataset-2 with feature size 6, **a** RMSE, **b** MSE, **c** MAE, **d** Accuracy

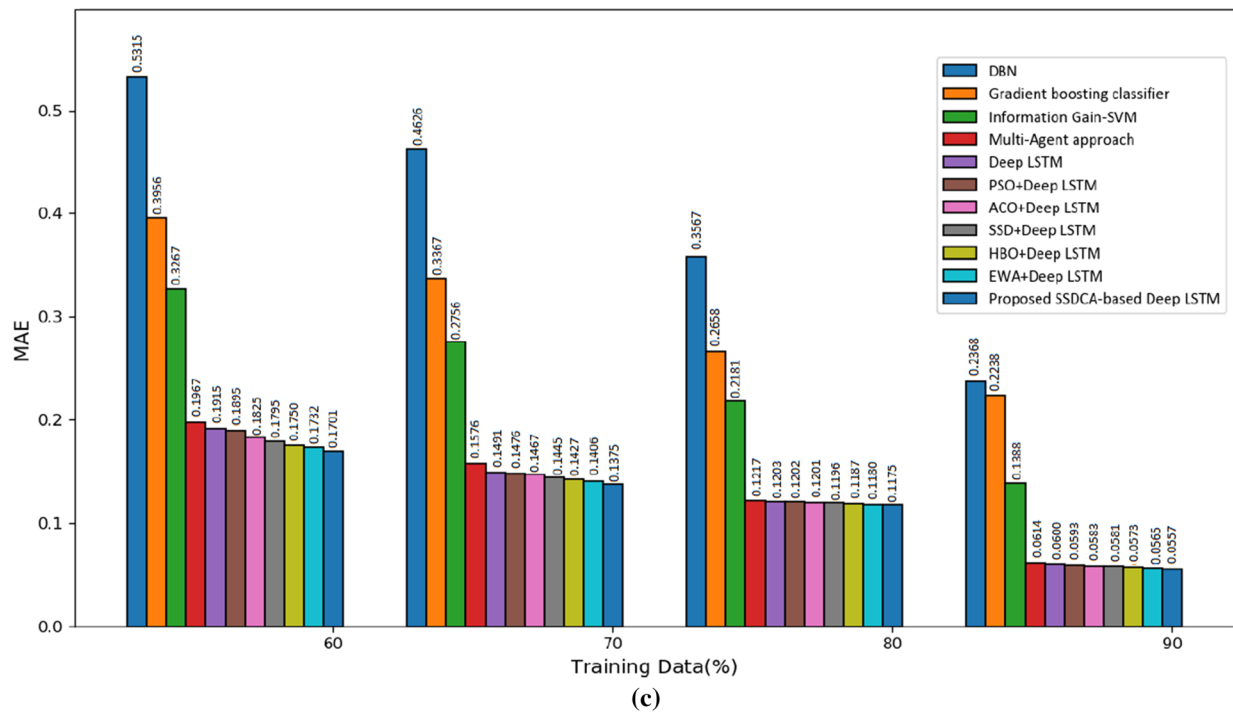
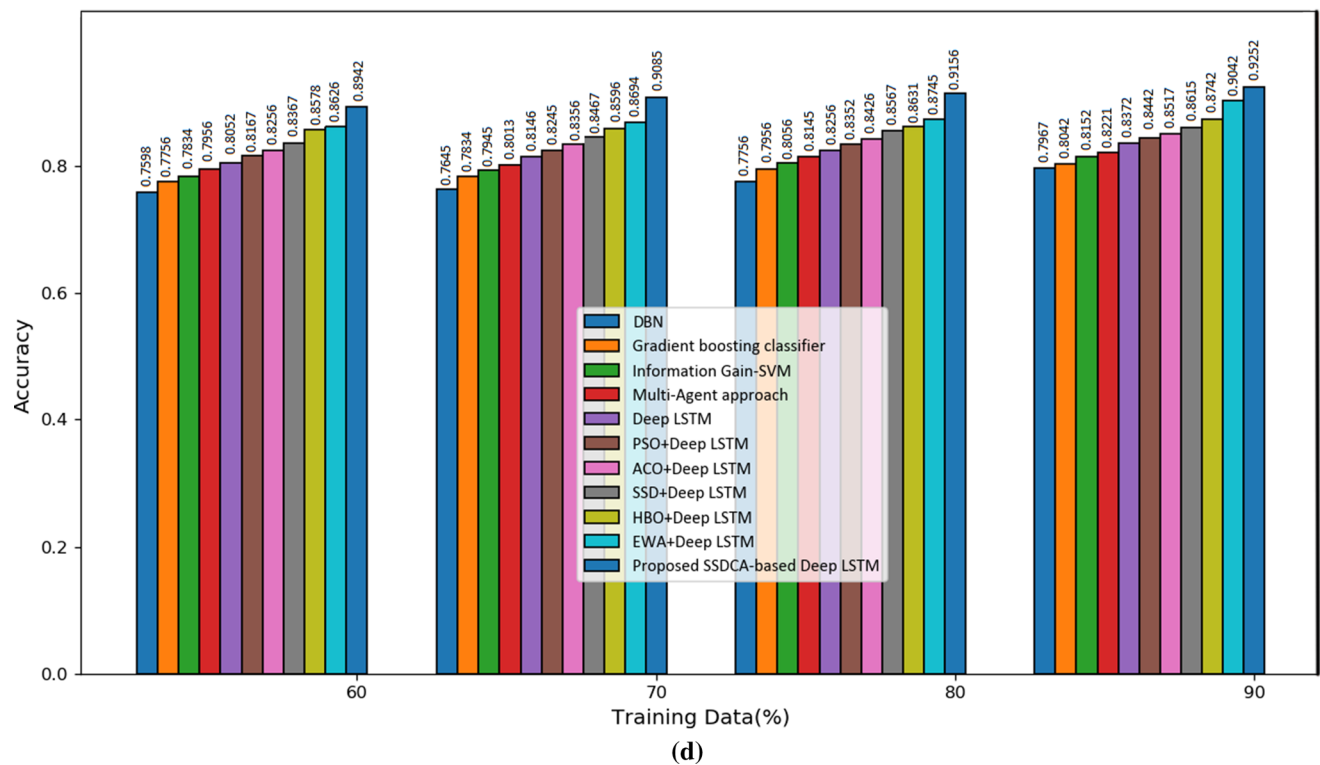


Fig. 10 continued

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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