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A review on long short-term memory combination development

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ABSTRACT

Long short-term memory (LSTM) has continued to develop since it was proposed in 1997. LSTM has optimized solutions to various problems. The LSTM cell, architecture, and memory model have been reviewed. A review of LSTM implementation has been carried out in various problem domains. There are combinations of LSTM with other methods to optimize solutions. However, there is no review on the development of LSTM combination (LC). This research reviews the development of the LC model on nine research questions, namely: development framework, data, preprocessing, learning process, tasks, optimization and evaluation, domain problems, trends, and challenges. The results show that the LC model is increasingly widespread in solving problems. The LC model has completed 26 types of tasks. Prediction, detection, forecasting, classification, and recognition are the most frequently performed tasks. LC model development trends show that LSTM is increasingly collaborative with other methods on a wider scope. The challenges identified include research areas, data, model developments, the area of implementation, performance, and efficiency.

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1. INTRODUCTION

Long short-term memory (LSTM) is a recurrent connection network architecture that enables updating the current state based on past states and current input data. LSTM is a new method to address the weakness of recurrent neural network (RNN). LSTM consists of memory, input gate, forget gate, and output gate. LSTMs can be stacked to create deep LSTM networks that can learn more complex sequential data. LSTM is capable of learning more than 1000 steps in advance [1].

Two reviews on LSTM architecture focus on LSTM cells and LSTM component. The LSTM cell review aims to explore the learning capacity in dealing with long-term dependency problems. This review has found that no LSTM variant outperforms in all aspects [2]. The LSTM component review found it can be applied to interesting tasks, including text recognition, time series forecasting, natural language processing, computer vision, text, images, and video. This review found that the combination of LSTM and a convolutional neural network (CNN) can improve system performance optimization [3].

Two reviews on LSTM application focus on stock market prediction and anomaly detection. The LSTM application in stock market prediction review shows that LSTM plays an important role in stock market forecasting. This review recommends that LSTM should be combined with other methods to improve accuracy by considering external factors [4]. The LSTM application in anomaly detection review shows that different architectures are capable of detecting various complex anomalies contextually and collectively [5].

Both reviews above only discuss the LSTM cell architecture itself and have not discussed the combination architecture of LSTM with other methods. They only discuss the implementation of LSTM in a limited scope, even though LSTM has been implemented in a wide range of areas. This research will review the development of LSTM combinations (LC) in various areas and architectures. It will be conducted in the form of a systematic literature review (SLR) to ensure a more detailed and focused analysis. To achieve the main objectives, the following nine research questions were defined: i) RQ1: what is the LC model development framework?; ii) RQ2: how is the data used in LC model development?; iii) RQ3: how is preprocessing used in LC model development?; iv) RQ4: what is the learning process in LC model development?; v) RQ5: how to optimize and evaluate LC model development?; vi) RQ6: what tasks does LC model development perform?; vii) RQ7: what problems does the development of the LC model solve?; viii) RQ8: what is the recent trend in the development of LC models?; and ix) RQ9: what are the recent challenges in LC model development?

2. METHOD

This research has seven steps, namely formulating the problem, searching the literature, screening for inclusion, assessing quality, extracting data, analyzing, and synthesizing data as shown in Figure 1 [6], [7]. Text classification is used as the analysis technique [8]. Papers were obtained through a search process on several online academic search engines, such as Scopus, ScienceDirect, IEEE Xplore, SpringerLink, Emerald, and ProQuest, using the keywords "LSTM" with a filter for 2023, and the field of computer science.

The inclusion criteria used in this research include papers discussing the development of LC, papers containing a framework for developing LC to solve research problems in a particular domain, papers explaining the tasks carried out by LC, and papers explaining data and performance. Meanwhile, the exclusion criteria used in this research are papers containing the words "LSTM" or "Long short-term memory" in the title. The paper is a publication of research or experimental results. The stages of selecting papers based on inclusion and exclusion criteria are shown in Figure 2.

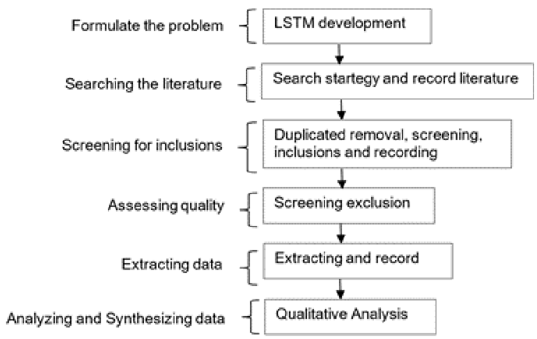

Figure 1. Research method

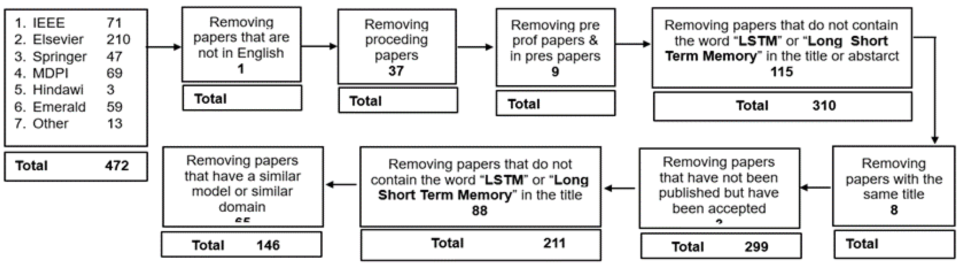

Figure 2. Stages of selecting papers

3. RESULTS AND DISCUSSION

This research focuses on reviewing the LC in SLR form in a more detailed and focused manner. Previous reviews only covered LSTM in a limited scope and in the form of general reviews that were less focused and detailed. This research describes the papers used, the results of the LC review, comparative reviews, and further research. The paper description is used to indicate the quality and quantity of research sources. The results of the review are used to show a description of LC model development from various predetermined points of view. Comparative reviews were used to demonstrate the recency and superiority of the review carried out compared to previous reviews. Further research is needed to refine the limitations of this research.

3.1. Papers description

Papers were collected through online academic search engines, including Scopus, ScienceDirect, IEEE Xplore, SpringerLink, Emerald, and ProQuest. All papers were published in 2023. The papers synthesized in this study have gone through 9 stages of selection with inclusion and exclusion criteria. The selected papers were 146 out of 472, or 30%. Figure 3 shows that the synthesized papers were published in 55 popular international journals. Most of the papers are published in journals in the field of computer science, with others in the field of applied computer science. 33% of the papers were published by journals in the field of computer science and its applications, including IEEE Access, Sensors, Energies, Applied Science, and Biomedical Signal Processing and Control. The quality of selected journals and paper publishers spread across eight countries is shown in Figures 4 and 5. Most of the papers were published by MDPI, IEEE, Elsevier, and Springer. Figure 6 shows that all journals occupy quartile one or quartile 2 in the Scimago Journal and Country Rank.

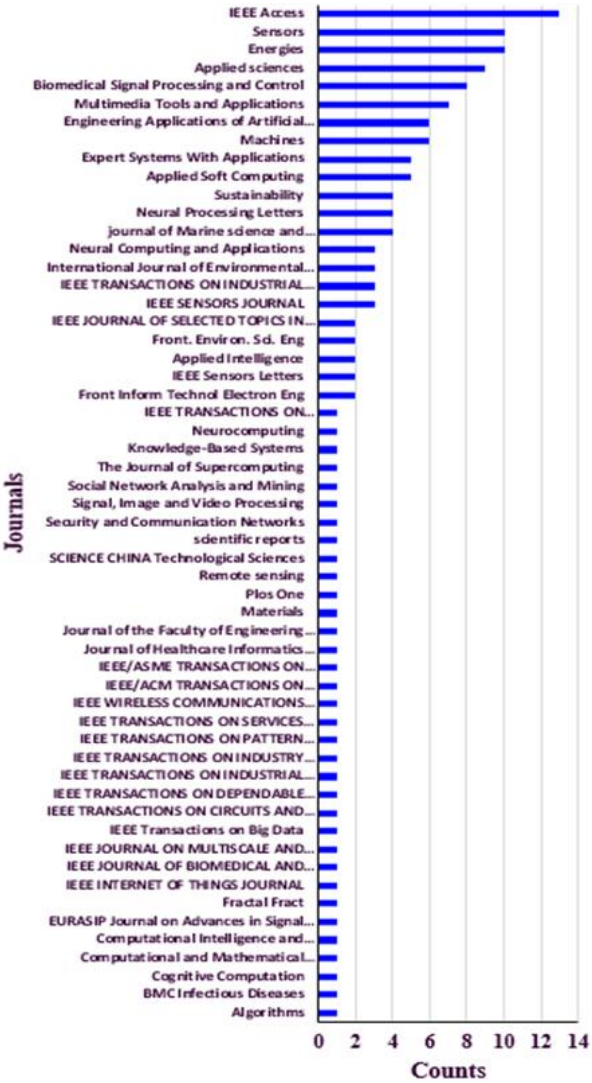

Figure 3. Publication journal of LC

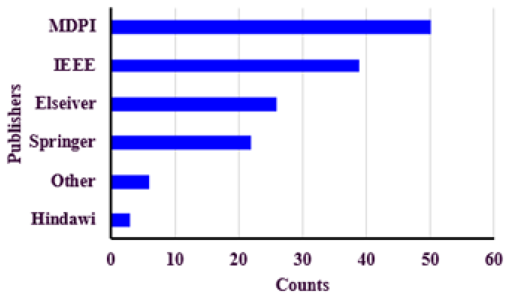

Figure 4. Publisher of LC

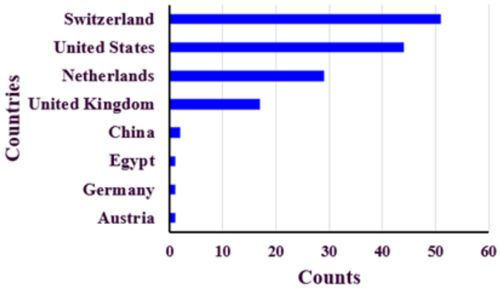

Figure 5. Publication country of LC

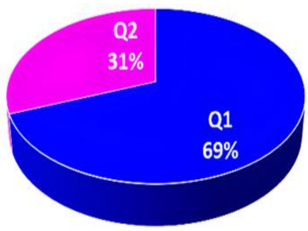

Figure 6. Journal quartile of LC

3.2. Research result

This research aims to describe the development of the LC model, including the framework, data, preprocessing, learning process, optimization, evaluation, tasks, problem domains, trends, and challenges, which were not discussed in previous reviews. The description of research results is accompanied by a discussion to present the research results more comprehensively. The discussion scope of the research results was based on nine predetermined research questions.

3.2.1. RQ1: what is the LC model development framework?

We found that LSTM development can be classified into two development models, namely development in LSTM cells and LC model development, as shown in Figure 7. LSTM cell development is carried out by modifying the architecture, weights, or functions of the LSTM cell. LC model development is carried out by combining LSTM with itself or combining LSTM with other methods. The combination of LSTM with other methods can be serial, parallel, or mixed.

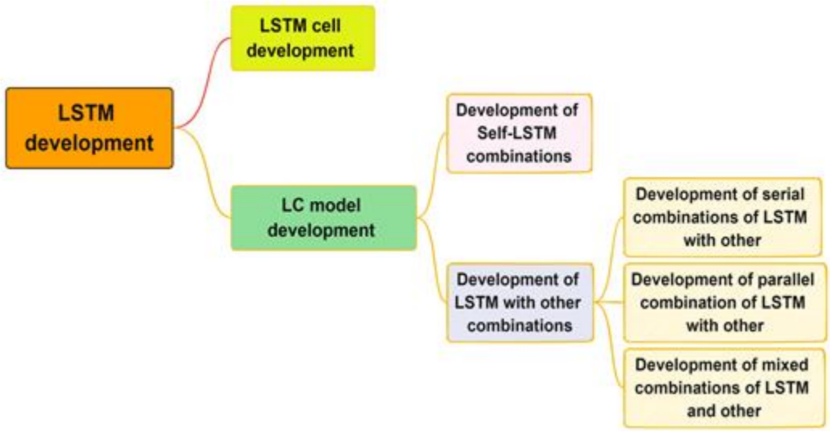

Figure 7. Classification of LC model development

The development of LSTM cell is less than LC model. The development of LSTM cells aims to optimize network models [9]–[12] and hidden layer optimization with certain algorithms, including particle swarm optimization (PSO) and genetic algorithm [13]–[17] or modifying network weights [18], [19]. For example, two sigmoid functions and the tanh function in the LSTM cell are replaced with a sinusoidal function to increase accuracy in problems whose output is periodic, and the use of Radix-r offset binary coding (OBC) as a recurrent connection weight at each gate of the LSTM cell to increase the exponential growth of the model size. LC model development can be classified into two models, namely, a combination of LSTM with itself [20] or a combination of LSTM with other methods. Most LC model developments are a combination of LSTM and one or more other methods [21]–[23]. The LC model format is serial [24]–[27], parallel [28]–[34], or a mixture [35]. The LC model development aims to get better model performance, but there are anomalies in certain cases [36].

We found the general LC development architecture as shown in Figure 8. The architecture is divided into three stages: data preparation, training model, and evaluation model. These three stages are related serially. Data preparation consists of data collection and data reduction.

The reduced data is saved as a dataset and ready to be used for the next process. Collecting data can be challenging due to difficulties in finding sources and extracting data, as well as dealing with diverse forms and types of data. The training model consists of input features, dividing training data and validation data, and learning processes. Some LC model developments carry out preprocessing [37], [38], feature extraction [39]–[41] or both. Feature engineering is the process of transforming raw data into a format suitable for analysis. This involves extracting necessary features using specific methods. The development of the LC model is further demonstrated by the learning process architecture. Optimal model performance is obtained from repeated training and validation, as well as modifying the proportion of training data and validation data. Training a model involves finding the best hyperparameters for optimal performance. The evaluation model aims to measure the performance of the LC model. The evaluation method for a model should be appropriate for its input, output, and tasks to understand its performance. Choosing a baseline method for comparison is a key challenge.

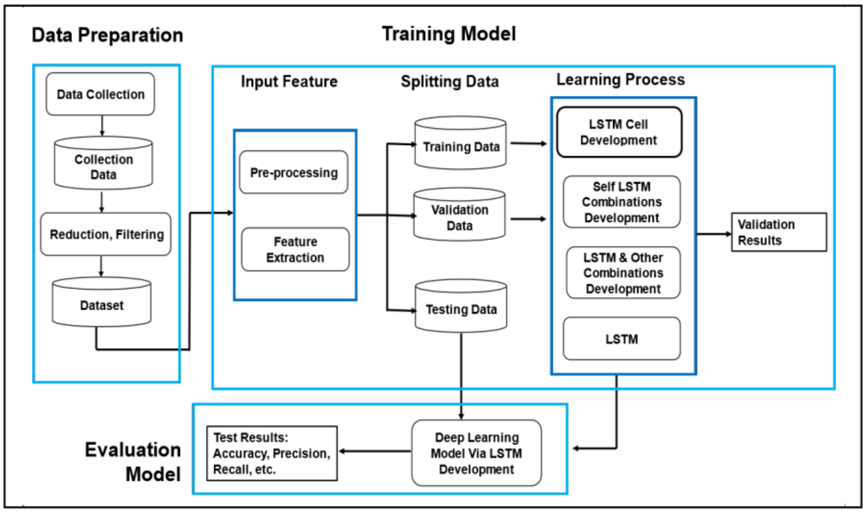

Figure 8. LC development framework

3.2.2. RQ2: how is data used in LC model development?

We found that the data used for developing the LC model can be classified into three categories, namely public datasets, official data, and experimental data. Figure 9 shows the proportions of the three data categories. Experimental data occupies the highest proportion. This proportion shows that most of the LC model development is based on real-world problems and laboratory tests [42]–[45]. Public data used for LC model development include IEEE bearing dataset [11], the DeepMIMO dataset [46], C-MAPSS dataset [47], BSL dataset [48], a publicly available dataset from New South Wales [49], weather dataset in Quinland [50], PHM2010 tool-wear dataset [51], new plant disease dataset [52], and IMDb [53]. The high proportion of official data usage indicates that the development of the LC model solves institutional business problems. Official data used for LC model development include the National Marine Data Center [54], experimental data from the University of Cincinnati's Intelligent Maintenance Systems Center [55], air pollution data, and meteorology data from 35 monitoring stations in Beijing [56], price of China Real Estate Index [57], Epilepsy Research Center at Bonn University in Germany [58], and actual operation data of Denmark's DK1 region in the Nordic electricity market [59].

We also found that the data used in LC model development can be classified based on its type as shown in Figure 10. The numerical data type is the most widely used, reaching 14% [60]–[62]. Meanwhile, the signal data type [63] is 20%, and the image data type [64] is 14%. Text and multivariate data types [65]–[67] each account for 10%. There are only a few other data types, including video [26], symbols [68], [69], and speech [70].

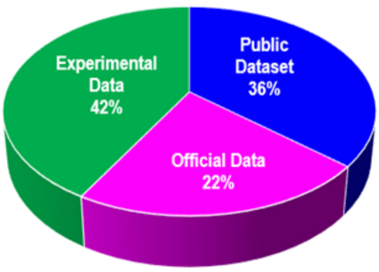

Figure 9. The data source of LC

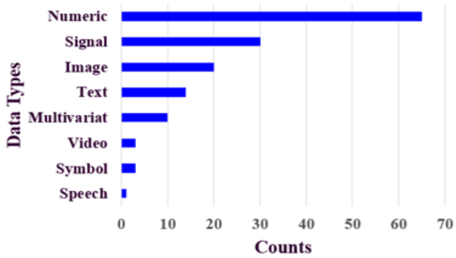

Figure 10. The data type of LC

3.2.3. RQ3: how is preprocessing in LC model development?

Most of the data cannot be analyzed directly in the learning process of LC model development. We discovered various methods of preprocessing data, as shown in Figure 11. These methods include Pearson correlation [41], normalization [71], interpolation [72], labeling [73], wavelet [74], word2vec [75], and converting, GloVe [76]. The need for preprocessing methods is determined based on the data type, data cleaning, and analysis method to be used [27], [77]. Some LC model developments use more than one preprocessing method [78]. Normalization is the most widely used method [79]. Some LC model developments use a combination of normalization and other methods [80], [81]. Preprocessing for text data uses GloVe [29], [76], or word2vec [82], while preprocessing for signal data uses wavelets [38], [74], or interpolation [83], [84]. Preprocessing in the LC-supervised model development model uses data labeling [85], [86].

3.2.4. RQ4: what is the learning process in LC development?

We found that LC model development is carried out by combining LSTM with modules, algorithms, or other methods to improve performance in problem-solving. Modules that are often used in LC model development include attention [21], [29], [35], ReLu [22], [23], pooling [24], [30], SoftMax [26], [39], conditional random field (CRF) [29], dropout [30], [80], flatten [31], [52], fully connected [47], [59], dense [50], [78]. Methods that are often combined with LSTM include CNN [21], [24], [28], RNN [69], transformer [42], [64], gated recurrent unit (GRU), and LSTM itself [20], [32], [56]. BiLSTM and StackedBiLSTM are examples of LC methods themselves [87]. Multi-layer sequential LSTM and multi-head LSTM are combinations of LSTM themselves in sequential [88]. CNN is the most often used method in LC models, as shown in Figure 12.

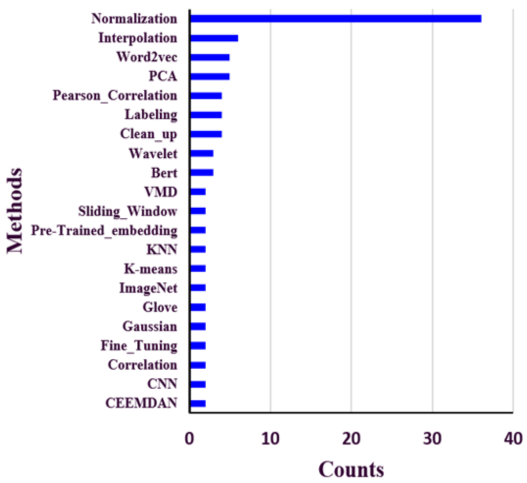

Figure 11. The methods used in LC preprocessing

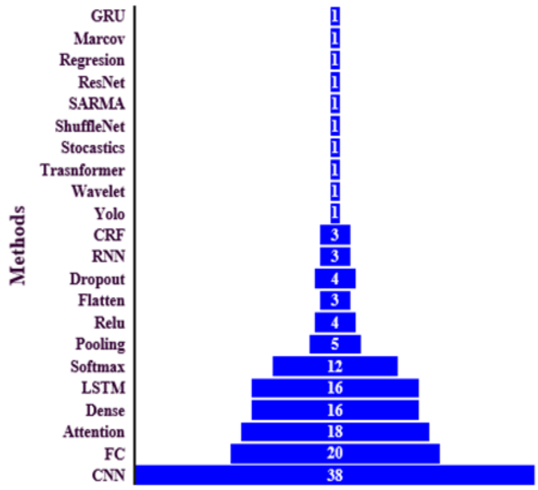

Figure 12. The method combined with LSTM in LC learning

Three types of LC are serial combination, parallel combination, and mixed combination. MC-LSTM [27], ER-LSTM [80], CNN-LSTM [88], and BiLSTM-Softmax [89] are examples of the LC serial combinations. CNN-BiLSTM [29], ACN-LSTM [30], hybrid 1DCNN-LSTM [31], and CNN-LSTM [82] are examples of the LC parallel combinations. Reusable LSTM network (RLN) [32], Hybrid CNN-LSTM with multi-level attention fusion [74], distributed ensemble LSTM [75], and EPKSL [90] are examples of the LC mixed combinations.

3.2.5. RQ5: how to optimize and evaluate LC model development?

Some LC model developments use optimization methods to improve model performance. Figure 13 shows the proportion of algorithms discovered for optimizing LC model development. The PSO and Adam algorithms are the most often used for this purpose. An LC model using PSO can produce good performance, as it achieved a high F1-score [91]. Developing an LC model using the Adam algorithm can also lead to good performance, with high F1-score, accuracy, and AUC [70], [89], [92].

All LC model development goes through a model evaluation cycle. Figure 14 shows the proportion of evaluation methods discovered in LC model development. The most often evaluation methods are accuracy, root mean squared error (RMSE), and F1-score. Several LC model developments have achieved high accuracy, approaching 99% [93]–[95], but there are still models with accuracy under 72% [96]. Some LC model developments have achieved relatively small RMSE [97], [98], but there are still models with high RMSE [99]. Several LC developments have achieved high F1-scores [100]–[102], but there are still models with low F1-scores [103].

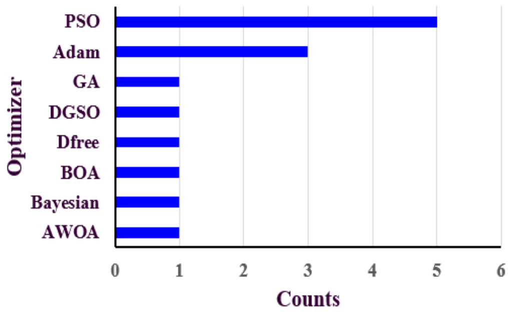

Figure 13. Optimization algorithms in LC

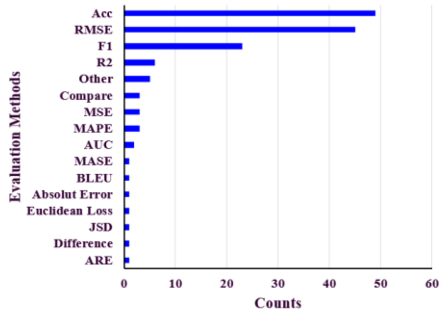

Figure 14. Evaluation method in LC

3.2.6. RQ6: what tasks does LC model development perform?

The development of the LC model was carried out to complete certain tasks in solving problems in the real world. This model has completed various tasks. Five main tasks that are often carried out in LC model development include recognition [12], [26], [80], [85], [86], [100], prediction [104]–[106], detection [107], [108], forecasting [109]–[114], and classification [115]–[117] as shown in Table 1. Other tasks performed by LC model development in a limited scope include analysis, modeling [118], optimization [119], sensing, and diagnosis. Prediction is the task most LC model development performs.

Table 1. The proportion of LC development tasks

No	Task	Proportion (%)
1	Prediction	23
2	Detection	14
3	Forecasting	14
4	Classification	12
5	Recognition	8
6	Various others task	29

3.2.7. RQ7: what problems does the development of the LC model solve?

Problems in the real world are numerous and rapidly developing. Various developments have been carried out to solve these problems. We found that the development of the LC model has penetrated various real problem areas in the world, as shown in Figure 15. These problem domains include the environment, mechanical, electrical, health, and financial. Environmental problems include urban water [38], urban flooding [45], water pollution [109], domestic waste generation [114], and transportation [120]. Mechanical problems include servo systems [66], missile maneuver trajectories [67], aircraft engines [71], and machine cutterheads [121]. Energy problems include solar power [105] and wind power [122]. Industrial problems include chemical processes [18], gas analysis [94], and complex product design [118]. Health problems include drug reactions [19], cardiovascular issues [88], brain tumors [95], food safety [103], and influenza [123].

Human-style problems include facial emotions [26], sleep staging [33], gait phases [86], and driving style [115]. Financial problems include China's real estate stock trend [57], stock price [98], and credit card fraud [124]. Social media problems include text [53], social networks [78], and Chinese news [82]. Agricultural problems include plant disease [52], tomato seed cultivars [125], and agricultural products [126]. Electrical problems include electrical consumption for ships [21] and electrical load [49]. Geography problems include lithology [16], fiber optic cable [93], ground motion [127], acute mountain sickness [128], and fault location [129]. Network problems include IoT environment [130] and cloud computing [131]. Maritime problems include ship motion [17] and wave height [54]. Image problems include hyperspectral image [64], image caption generation [132], and fused multimodality medical image [133]. Language problems include baby sign language [48] and multilingual humor and irony [76]. Electromedical problems include epileptic EEG signals [58], and EEG [134]. Other problems include partial discharge [25], multi-domain [75], and permafrost degradation [135].

3.2.8. RQ8: what is the recent trend in the development of LC models?

We found that the trend of data used in LC model development is getting closer to real-world problems. This is shown by the proportion of data, namely 64% collected from experimental data or official data, as shown in Figure 9. The development of the LC model using official data shows that LC model development is needed to provide solutions to business problems. LC model development using public datasets aims to find the best performing. The trend of LC model development based on research problem domains shows that the scope of LC model research is increasingly broad, as shown in Figure 16. This shows that all areas of research are possible to carry out through the development of LC models. Meanwhile, the trend of LC model development based on the tasks shows that LC development is used to solve prediction, detection, forecasting, classification, and recognition tasks. We found that the trend of preprocessing in LC model development is normalization, as shown in Figure 11. CNN is the most trending method for combining with LSTM in the learning process, as shown in Figure 12. Meanwhile, the trend of LC model development on testing results shows that LC model performance is still varied.

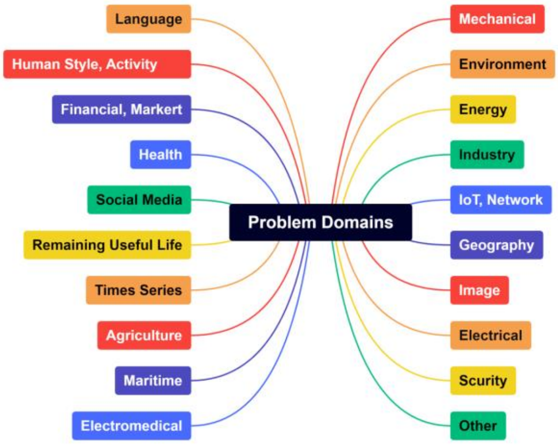

Figure 15. The problem domains solved by LC

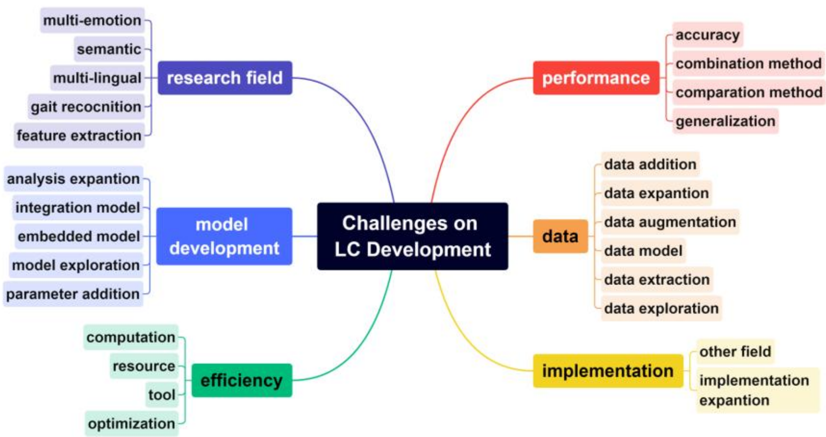

Figure 16. LC development challenges

3.2.9. RQ9: what are the recent challenges in LC model development?

We found that the challenges of developing an LC model related to data problems include data growth, data expansion, data exploration, data augmentation, data modeling, and data extraction, as shown in Figure 16. Further data growth studies were carried out to increase the amount of data [136], [137]. The growth of data requires further studies on augmentation [81] or exploration [102]. Further studies on data expansion were carried out by expanding the scope and range of data [138]–[140]. Further studies on data modeling and data extraction are needed to simplify the processing and representation of data [76], [117], [125].

Challenges in LC model development related to improving model performance include increasing accuracy, enhancing generalization ability, conducting method combination trials, and comparing combination methods. Further research related to accuracy includes involving uncertainty theory [141], increasing data from multiple sources [56], [128], combining various methods [39], [83], [84], [99], [124], and comparing them [111]. Additional studies related to generalization involve using more complex data [18], larger datasets [95], additional equipment [142], and integrating ideas and parameters into models [121]. A significant issue in LC model development is efficiency. Further research related to model efficiency includes computation, resources, tools, and optimization. Computational challenges include algorithms, calculations, and time complexity [19], [88], [109]. Lack of resources and poor tool quality are ongoing issue in LC model development [85], [100], [133], [143], [144]. Hot topics related to LC model development optimization include optimization techniques, structure optimization, algorithms, security, overfitting, and errors [23], [68], [69], [98], [112], [115], [118], [119]. Further research on LC model development can be conducted at the implementation level. Studying model implementation in various field is a fascinating area to explore [11], [41], [87], [91], [97], [131], [145], [146]. Expanding the scope of implementation is also a challenging study [58], [92], [129].

The development of the resulting LC model is a never-ending challenge. Challenges related to model development include analysis expansion, model integration, embedded models, and model exploration. Analysis expansion is carried out to increase the model's solution capabilities for the problems being solved [37], [75], [101], [113], [134], [147]–[149]. Model integration and embedded models are carried out regarding the use of resources or tools to make the model easier [29], [34], [53], [74], [150]. Further studies on model exploration include data exploration, techniques, resources, and algorithms so that the model provides more added value [31], [78], [79], [97], [104], [105], [108], [127], [151]. Another interesting challenge in LC development is parameter expansion. Parameter expansion aims to improve the model by considering other influential factors that have not been considered in previous models [40], [57], [71], [77], [90], [106], [107], [116], [122], [123], [126], [130], [149], [151]–[153]. The development of the LC model also depends on the specified research topic or field. Research fields that require further study include multilingual [82], gait recognition [86], multi-emotion [96], semantics [132], and feature extraction [154].

3.3. Discussion

This research specifically conducts a review paper that explains the development of the LC method. The papers selected for this research were filtered rigorously to ensure high quality. It provides a comprehensive description of the reviewed papers, demonstrating the level of quality of the papers used, which has not been done in previous reviews. The review applied an SLR method, which has not been used in any LSTM review. The SLR method gave a clearer and more focused review. Table 2 shows that this study explicitly finds a complete aggregation of LC development and outlines challenges for further research on LC. However, this research has limitations. The review scope is limited to the LC method only. The review includes papers published in 2023 with titles containing "LSTM" or "Long short-term memory". The review is limited to nine research questions. To enhance the review, additional research questions can be included, and more recent papers can be considered due to the rapid pace of research developments.

Table 2. Aggregation of LC development

Research question	Aggregation
Model development framework	Data preparation, training model, and evaluation model
Data source	Experimental data and public dataset
Data type	Numeric, signal, image, and text
Methods used in preprocessing	Normalization
Method combined with LSTM in learning	CNN, dense, attention, SoftMax, and ReLu
Optimization algorithms	PSO and Adam
Evaluation method	Accuracy, RMSE, and F1-score
Task	Prediction, detecting, forecasting, and classification
Problem domains solved	All domain
Recent trend in the development	Real-world problems
Recent challenges in the development	Research field, data, model, performance, and implementation

4. CONCLUSION

This SLR is based on 146 papers selected from Q1 or Q2-indexed journals in computer science in 2023. All papers contain "LSTM" or "Long short-term memory" in their title. The LC model development framework includes data preparation, preprocessing, learning, validation, and testing, with data mainly sourced from experimental or official sources. LC models aim to address real-world problems across various domains such as environment, mechanical, energy, network, industry, geography, electrical, health, human style, agriculture, and social media. CNN is a popular method in LC model development, and PSO is widely used for optimization. Research on LSTM cell development is limited. Prediction, detection, forecasting, classification, and recognition are common tasks in LC model development. Collaboration and integration of LSTM with other methods are trends in LC model development, offering solutions to real-world challenges.

Data expansion, performance enhancement, model comparison, research field expansion, and implementation are challenges in LC model development with diverse parameters and domains. This research addresses nine research questions. The review highlights the rapid growth of LC models, demonstrating the versatility of LSTM in solving complex real-world problems across various fields. Although LC development is increasingly complex, it provides promising opportunities to address challenges in solving real-world problems.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ahmad Riyadi	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		✓	✓
Nur Rokhman	✓	✓		✓		✓				✓		✓	✓	✓
Lukman Heryawan	✓	✓		✓		✓				✓		✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors confirm that there is no conflict of interest associated with this publication.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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