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Sina Ardabili – Amir Mosavi – Csaba Makó – Péter Sasvári

A COMPREHENSIVE REVIEW AND EVALUATION OF DEEP LEARNING METHODS IN THE SOCIAL SCIENCES

Sina Ardabili, Research Fellow, Ludovika University of Public Service, Institute of the Information Society, s.ardabili@ieee.org

Amir Mosavi, Research Fellow, Ludovika University of Public Service, Institute of the Information Society, Mosavi.Amirhosein@uni-nke.hu

Csaba Makó, Professor, Ludovika University of Public Service, Institute of the Information Society, mako.csaba@uni-nke.hu

Péter Sasvári, Associate Professor, Ludovika University of Public Service, Faculty of Public Governance and International Studies, Department of Public Management and Information Technology, University of Miskolc, Faculty of Mechanical Engineering and Informatics, Institute of Information Science, sasvari.peter@uni-nke.hu

Artificial intelligence (AI) is widely used in social sciences and continues to evolve. Deep learning (DL) has emerged as a powerful AI tool transforming the social sciences with valuable insights across many areas. Employing DL for modelling social sciences' big data has led to significant discoveries and transformations. This study aims to systematically review and evaluate DL methods in the social sciences. Following PRISMA guideline, this study identifies fundamental DL methods applied to social science applications. We evaluated DL models using reported metrics and calculated a normalised reliability score for uniform assessment. Employing relief feature selection, we identified influential parameters affecting DL techniques' reliability. Findings suggest that evaluation criteria significantly impact DL model effectiveness, while database and application type influence moderately. Identified limitations include inadequate reporting of evaluation criteria and model structure details hindering comprehensive assessment and informed policy development. In conclusion, this review underscores DL methods' transformative role in the social sciences, emphasising the importance of explainability and responsibility.

Keywords:
social science, deep learning, big data, machine learning, artificial intelligence, generative artificial intelligence

INTRODUCTION

The integration of artificial intelligence (AI) in the social sciences is expanding rapidly, profoundly shaping the field. AI equips researchers with powerful tools to analyse vast and complex social datasets with greater accuracy and efficiency. AI's application in the social sciences is becoming increasingly prevalent and transformative, offering valuable tools for analysing intricate social data. Machine learning (ML) and deep learning (DL), as the fundamental AI tools are revolutionising the social sciences, providing unprecedented opportunities for analysis and insight. This merging of technologies with social science methodologies represents a pivotal moment in research, enabling scholars to explore complex societal phenomena with enhanced depth and precision. ML and DL provide a robust toolkit for social scientists to uncover meaningful patterns and relationships from diverse datasets. This is the reason we refer to the current decade as the golden age of social sciences.[1] ML algorithms, including deep neural networks, decision trees and support vector machines, can reveal hidden structures and trends within social data, facilitating tasks like classification, prediction, and clustering. By utilising these tools, researchers can gain fresh insights into human behaviour, societal dynamics and cultural trends. DL, a subset of ML, holds particular promise in social science research due to its capacity to automatically learn hierarchical representations from data. DL techniques are increasingly applied in the social sciences to analyse large-scale textual data from social media platforms, revealing sentiment trends, identifying social networks, and understanding public discourse. Additionally, DL models can process multimodal data, integrating text, images, and videos to offer a more comprehensive understanding of social phenomena. Moreover, DL enables the integration of diverse data sources and methodologies in social science research. By merging structured data from surveys and administrative records with unstructured data from textual sources and social media, researchers can gain a holistic view of human behaviour and societal trends. Furthermore, AI-driven methods facilitate the integration of quantitative and qualitative approaches, bridging disciplinary boundaries and fostering interdisciplinary collaboration in social science inquiry. In essence, the application of DL in social sciences ushers in a new era of discovery and innovation, providing unprecedented opportunities to understand and address complex social issues. By harnessing the power of ML and DL, social scientists can advance knowledge, inform policy, and contribute to societal improvement. Social science is experiencing a golden age, marked by explosive growth in new data and analytic methods, interdisciplinary approaches, and a recognition

[1] Miller 2019; Grimmer et al. 2021; Buyalskaya et al. 2021.

of their necessity in solving the world's most challenging problems. Computational social science[2] has risen in prominence over the past decade, with thousands of papers utilising observational data, experimental designs, and large-scale simulations that were once unfeasible or unavailable to researchers. These studies have significantly enhanced our understanding of social sciences.

With abundant data and an increasing reliance on DL, social scientists are re-evaluating applications and best practices. Unlike traditional tasks in computer science and statistics, DL applied to social scientific data aims to discover new concepts, measure their prevalence, assess causal effects, and make predictions. The abundance of data facilitates a shift from deductive social science toward a more sequential, interactive, and ultimately inductive approach to inference. Historically, empirical work in social sciences was constrained by scarcity, where data, surveys, and computational resources were limited. However, the current landscape is defined by abundance, with big data transforming the evidence base. Social scientists are increasingly turning to deep learning methods to leverage this abundance, prioritising performance on established quantitative benchmarks. DL methods offer transformative potential in the social sciences, necessitating a re-evaluation of conventional practices. This involves reapplying deep learning techniques to gain insights into social science big data. The current abundance of data allows for a shift toward a more inductive approach, characterised by sequential and iterative inferences.[3] Using DL is crucial in social science research today. DL contributes in processing and analysing large datasets, uncovering patterns and relationships within social phenomena.[4] These technologies support evidence-based decision-making, improve prediction accuracy, and offer new perspectives on human behaviour and societal dynamics. DL is used in areas such as sentiment analysis, opinion mining, and social network analysis. Big data analytics helps to understand social trends and demographic changes, while DL allows the analysis of unstructured data like text and images. These technologies work together to enhance researchers' ability to understand and predict complex social phenomena. Reviewing the application of deep learning in social sciences can help identify successful applications, evaluate effectiveness, and highlight research gaps and opportunities. Ethical considerations are essential, ensuring responsible use of these technologies.[5] A comprehensive review provides valuable insights for policymakers, informing policies on data privacy, algorithmic transparency, and responsible implementation of deep learning. Consequently, this article provides an overview of how social scientists utilise DL methods and evaluate model performance. Several review studies on the applications of ML and DL have been conducted in various sections of the social sciences. Table 1 summarises these studies. Nevertheless, a review that is systematically following a standard guideline, which includes the evaluation of the method is missing from the literature.

2 Lazer et al. 2020; Moon–Blackman 2014.
3 Hofman et al. 2021; Galesic et al. 2021; Zhang et al. 2020.
4 Poole–Mackworth 2010; Al-Sartawi 2021.
5 Lecun et al. 2015; Goodfellow et al. 2016.

Table 1: Notable DL- and ML-based review studies in the social sciences

Ref.	Description	Limitations	Systematic review	Review guideline	Evaluational viewpoint
Rani–Sumathy 2022	To analyse DL and ML techniques in Sentiment Analysis	Single field	✓	x	x
Özerol–Selçuk 2022	To study the ML and AI techniques in analysing the relationship between machines and humans	Single field	✓	x	x
Bai–Bai 2022	To study the role of ML in Sports Social Networks	Limitation of analysis	x	x	x
Nasir et al. 2021	To analyse the trend of Financial Technology using ML	Single field and limited applications	✓	x	x
Khan–Ghani 2021	A Survey of DL for Human Activity Recognition	Limitation of analysis	✓	x	x
Kumar et al. 2021	ML and DL for analysing Online Social Network Security	Limitation of performance analysis	x	x	✓
Present study	Evaluation of DL in different applications of social science	We did our best to cover the limitations of previous studies	✓	✓	✓

Source: compiled by the authors

METHODOLOGY

Database preparation

The database was created using Scopus and further refined employing PRISMA guideline,[6] and Selçuk (2019) as a guideline. The search syntaxes included the terms deep learning and further deep learning general algorithms, e.g. convolutional neural network, long short-term memory, deep neural network, deep belief network, recurrent neural networks, and deep reinforcement learning, employed for social science (see Table 2). The subfield of DL and its applications in the social sciences was investigated using a comprehensive search filter. Table 2 indicates the search queries within article titles, abstracts, and keywords using AND, OR/AND operators.

[6] Page et al. 2021.

Table 2: Searching queries from databases

Search within	Operators	Keywords
Article title, abstract, keywords	OR	(deep learning, convolutional neural network, long short-term memory, deep neural network, deep belief network, recurrent neural networks, and deep reinforcement learning)
Article title, abstract, keywords	AND	(social science and the related keywords)

Source: compiled by the authors

The PRISMA guidelines have four main phases including 1. identification phase, 2. screening phase, 3. eligibility phase and 4. inclusion. Figure 1 presents a flowchart of the PRISMA guidelines for the present research principles.

The main prospect of this review is to evaluate the DL-based techniques in the different applications of social science. The 1st phase of the PRISMA guidelines (Identification phase) involves identifying the required cases and building the database (Figure 1, 1st Phase). Accordingly, about 511 cases, 482 cases (about 94% of total cases) were exported from the WoS, and Elsevier Scopus, and 29 cases (about 6% of total cases) were exported from the other databases. Figure 2 presents the statistical trend of the records in the field per year. According to Figure 2, the trend of cases published is rising significantly. Figure 3 presents the progress of a decade of DL in social science. Figure 4 presents the geographical

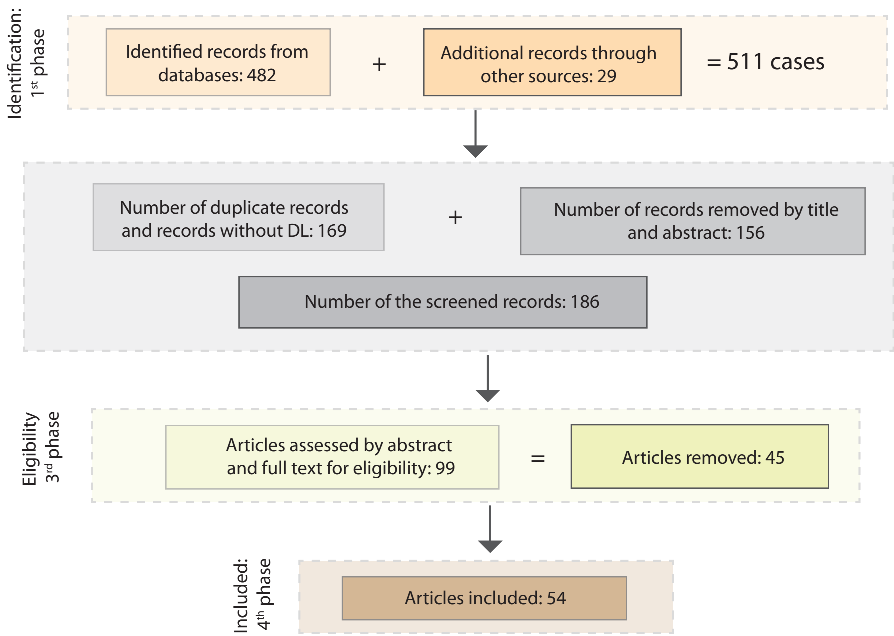


Figure 1: PRISMA guideline for preparing the database of the study
Source: compiled by the authors

Studies

distribution of the DL for social science. It is worth mentioning that social science closely interacts with various scientific and applied fields including medical, pharmaceutical and engineering fields. One of the challenges is to exclude the irrelevant studies from the database. However, in many cases due to interaction of various fields, this remains as a challenge and identified as a limitation of this study. Thus, including several irrelevant studies is inevitable.

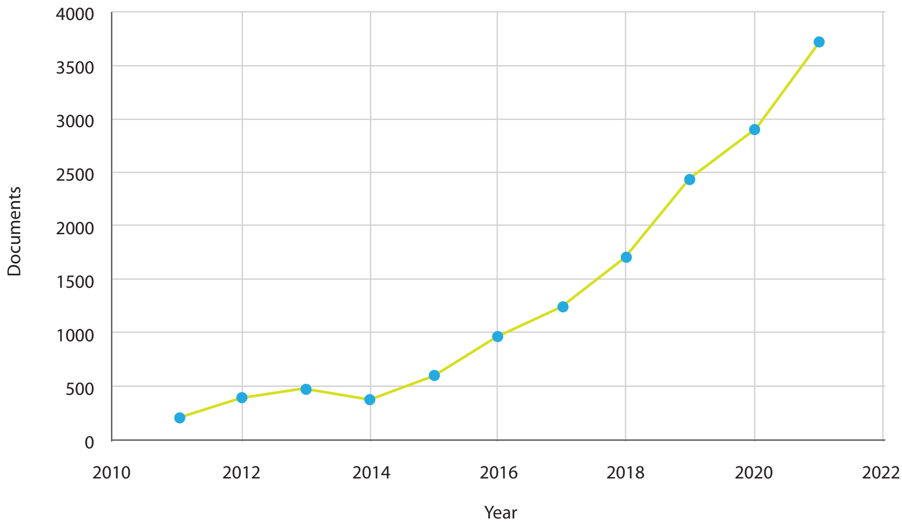


Figure 2: Progress of a decade of AI in social science
Source: compiled by the authors

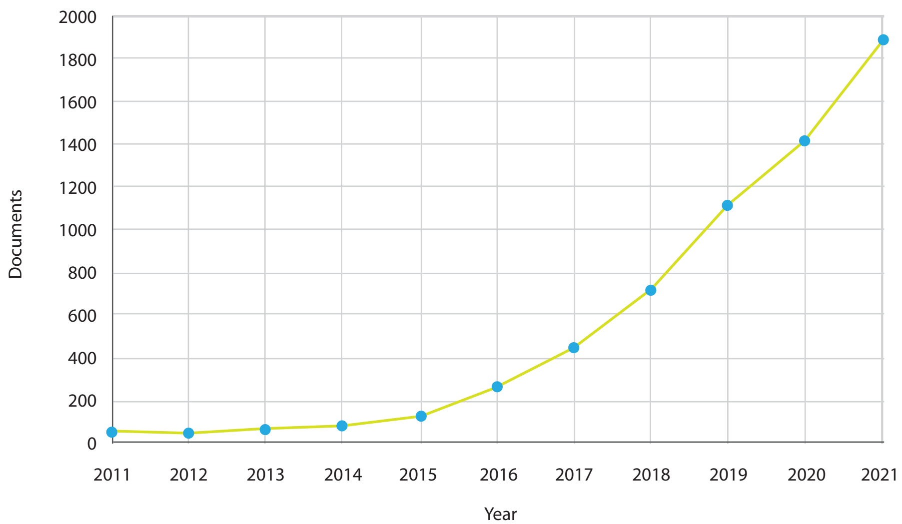


Figure 3: Progress of a decade of DL in social science
Source: compiled by the authors

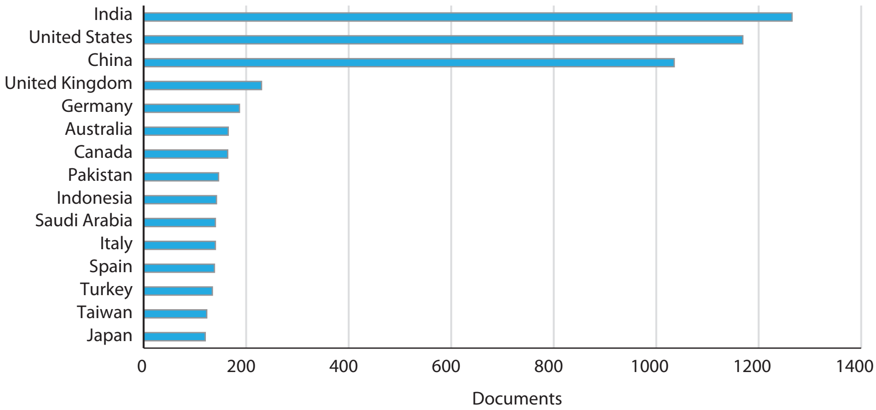


Figure 4: Geographical distribution of DL for social science
Source: compiled by the authors

In the 2nd phase of the PRISMA guideline, i.e. the screening phase, the duplicate cases, irrelevant cases, and cases without any information about DL are eliminated. In the 2nd phase, 169 cases were removed during the screening for duplication and 156 cases were removed by considering the title and abstracts. Figure 5 presents a bibliographic network based on the frequently used keywords after the first phase filtration, which were extracted as a map from bibliographic data by supporting WoS and Scopus databases.

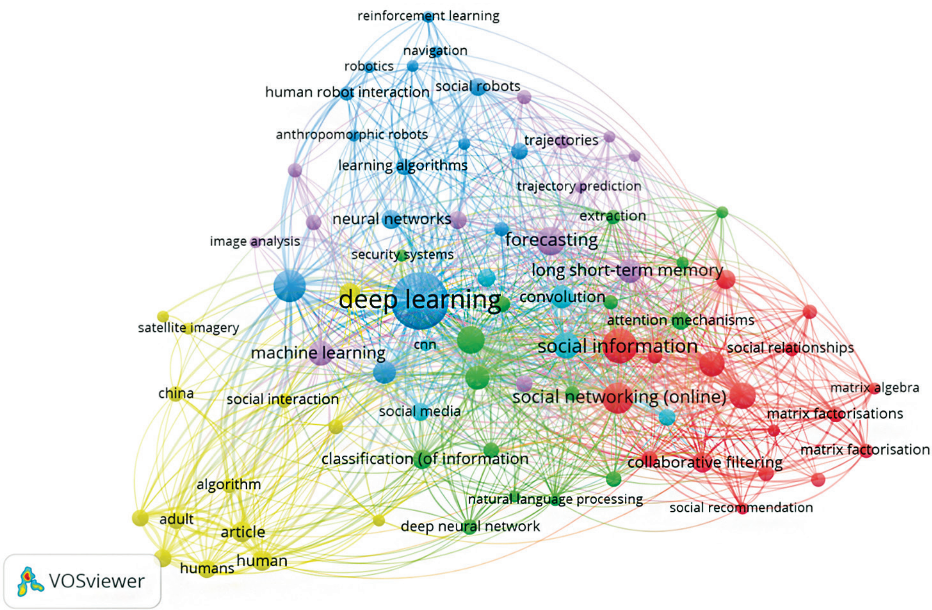


Figure 5: Bibliographic map of frequently used keywords
Source: compiled by the authors

Studies

In the following step, 186 cases were considered in the 3rd Phase (eligibility phase). The 3rd phase takes into account eligibility to filter the relevant articles. In this phase, the authors considered the full text of the cases, and the most relevant cases were chosen. Accordingly, 99 cases were selected for further evaluation. In some cases, there were limitations in accessing the full text of the records, especially in conference articles. In the last phase, 54 cases (about 11% of total cases) were selected for possible further evaluation. This "including phase" is the last step in the PRISMA guidelines. Finally, by analysing the included cases, the main taxonomy of the study was prepared. The materials studied were categorised into twelve subsets of the social sciences including social information, social network, social development, social movement, social inequalities, social cooperation, social conflict, social technology, social health, social risk, social environment, and social media (Figure 6).

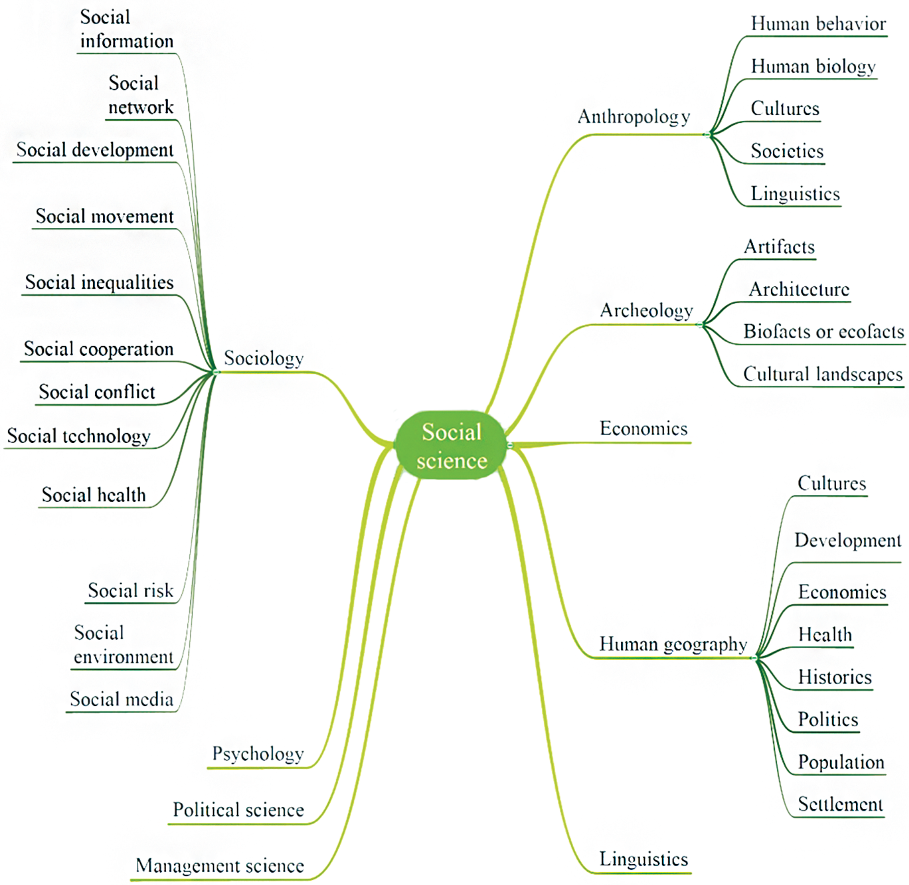


Figure 6: The subsections of social science
Source: compiled by the authors

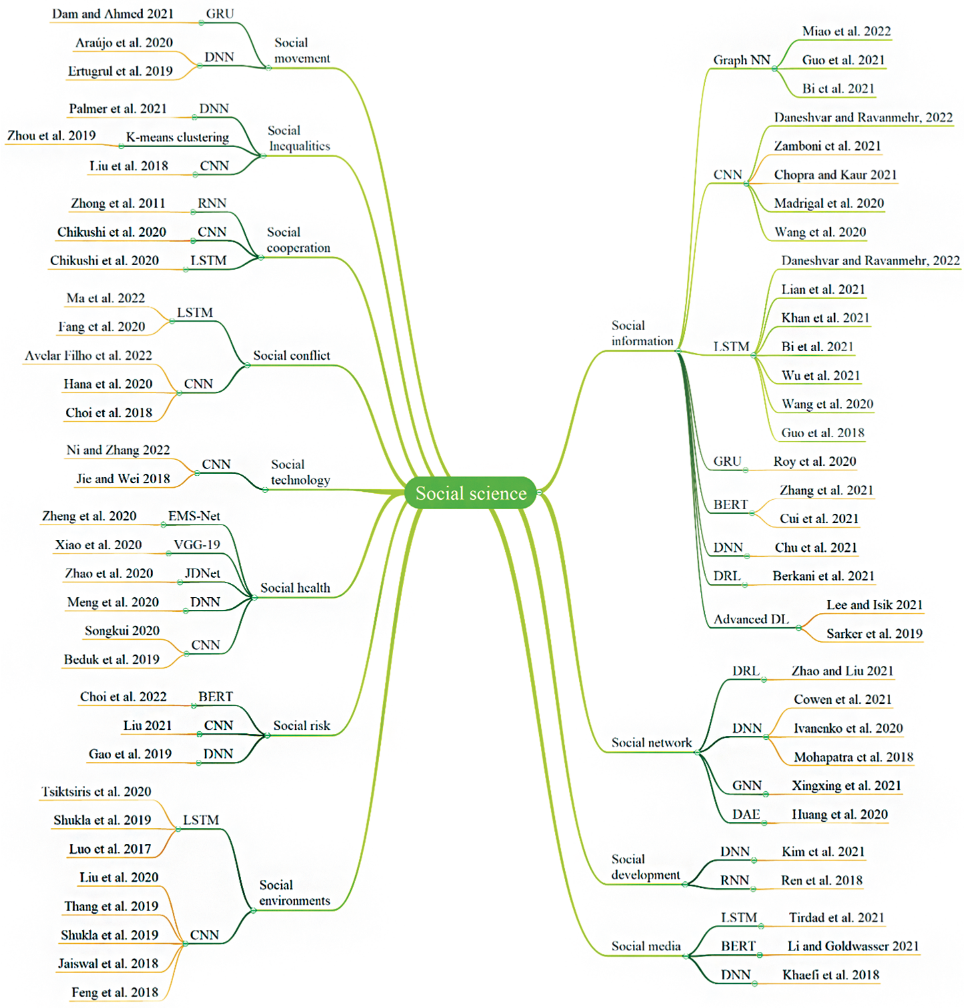


Figure 7: The main taxonomy of the study
Source: compiled by the authors

The next section presents the studies in each application of the social sciences. This section analyses the DL techniques in each section separately to highlight information along with the evaluation of the DL techniques employed (Figure 7).

Social information

Social information is one of the most frequently used keywords in the social science. Information about the notable studies that employed DL in different applications connected to social information is presented in Table 3. It has nine columns, including References, year of publication, description of the study, model characteristics, DL method type, evaluation criteria, application type, and the main keyword. This format for preparing the table description was also applied to the other fields of social science. Table 3 indicates some of the limitations of the studies that were selected. The phrase "NA" refers to non-available content.

Table 3: Notable DL-based studies for social information analysis

Ref.	Year	Description	Model character	Method	Analysing data source	Evaluation criteria	Application	Keyword
Miao et al. 2022	2022	To model collaborative signals	Meta-path Enhanced Lightweight	GNN	Social graphs	NA	Detection	Social recommendation
Daneshvar–Ravanmehr 2022	2022	To develop a social hybrid recommendation platform	RSLCNet	CNN and LSTM	Data from MovieTweetings, Mise-en-scène, and OMDB	MAE and RMSE	Detection	Social recommendation
Zhang et al. 2022	2022	To model factors affecting the social recommendation	NA	SoGNN	Three real-world datasets from book marking, and Last.fm	Precison	Prediction	Social recommendation
Zamboni et al. 2022	2022	To develop a platform for the estimation of the pedestrian trajectory	NA	CNN and RNN	Public dataset	NA	Prediction	Trajectory prediction
Masson–Isik 2021	2021	To propose social interaction perception	Fully connected-kernel size	CNN	Pretrained on the ImageNet	Prediction performance score	Prediction	Social interaction perception
Zhang et al. 2021	2021	To develop a platform for urban function recognition	Various hidden layers and nodes	BERT	Social sensing data	Kappa index and accuracy	Recognition	Semantic risk

Ref.	Year	Description	Model character	Method	Analysing data source	Evaluation criteria	Application	Keyword
Cui et al. 2021	2021	To develop an application to provide automatically assistance capabilities of social network applications	NA	BERT	38,970 sellers' information	Accuracy	Classification	Social e-commerce
Chu et al. 2021	2021	Cardiovascular disease prediction	NA	DNN	834 patients from 2017 to 2020	AUC, accuracy, sensitivity, specificity	Prediction	Cardiovascular disease
Chopra–Kaur 2021	2021	To develop a platform for IoT-based group size estimation	Various hidden layers and nodes	CNN	Open source software projects from github	RMSE	Prediction	Recommendation system
Khan et al. 2021	2021	To evaluate the effect of depression diagnosis on Twitter	NA	Bi-LSTM	Twitter database	Accuracy	Detection	Depression analysis
Bi et al. 2021	2021	To model the social recommendation system	Diffnet	GNN	Ciao and Epinions dataset	MAE and RMSE	Detection	Social recommendation
Ludl et al. 2020	2020	To diagnosis of unusual human activities in urban areas	Two-layer LSTM with 32 frames	LSTM	Human movement data	Accuracy	Recognition	Pose estimation
Wu et al. 2020	2020	Popularity-aware content detection in a closed social network	NA	LSTM	300 million records including 2250 webpages spreading in WeChat	Accuracy	Prediction	Autonomous content placement
Cong 2020	2020	A platform to propose film and television culture	Fully connected layers: 200*64*32*32* 32*16*16*16	CNN	User data and video data	MAE	Prediction	Personalised recommendation
Diaz et al. 2021	2020	To develop a platform for speaker detection using social information	ResNet3D-34, ResNet3D-18	CNN	Raw pixels (RGB images) and motion (estimated with optical flow)	AUC	Detection	Audiovisual modeling, feature fusion
Bai–Cheng 2020	2020	To propose a multi-dimensional NN for social images classification	NA	3DNN	RGB and depth images from social network images	Accuracy, precision and recall	Classification	Multi-modal deep learning

Source: compiled by the authors

The main aim of the present study is to evaluate DL techniques in relation to social science, therefore, we categorised the analysis by exploring the application type and the evaluation criteria. Figure 9 presents the statistical report of the evaluation criteria. Based on Figure 8, Accuracy (about 36%) followed by AUC (about 18%) provided the highest proportion for evaluating the application of DL techniques in social information. Accuracy was employed for evaluating the Bidirectional Encoder Representations from Transformers (BERT) technique in the urban function recognition using.[7] BERT was also evaluated by the accuracy criteria for analysing the automatic assistance capabilities of social network applications.[8] Accuracy was employed for evaluating the deep neural network (DNN) for cardiovascular disease prediction.[9] The performance of the Bidirectional long-short term memory (Bi-LSTM) was evaluated by accuracy criteria to diagnose the effect of depression diagnosis on Twitter.[10] The performance of LSTM for the diagnosis of unusual human activities in urban areas was evaluated in terms of its accuracy.[11] Accuracy was employed as the criterion for evaluating LSTM in popularity-aware content detection in a closed social network.[12] Accuracy evaluated the performance of 3DNN to propose a multi-dimensional NN for social image classification.[13]

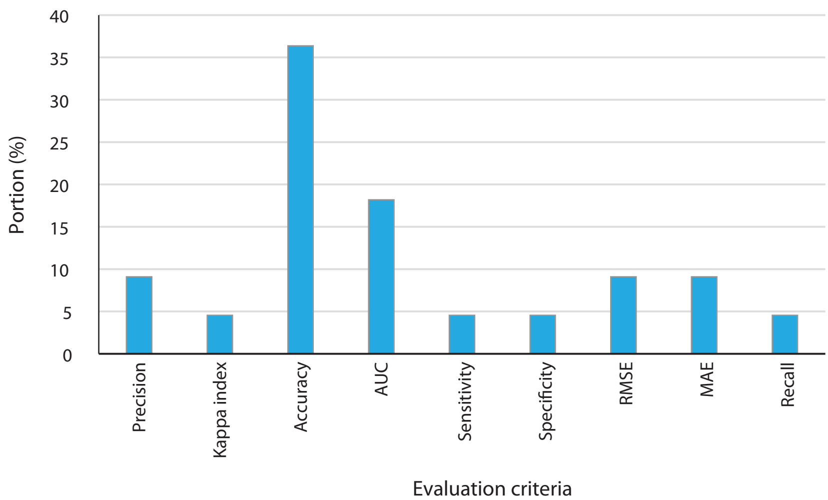


Figure 8: Statistical report of the evaluation criteria
Source: compiled by the authors

[7] Zhang et al. 2021.
[8] Cui et al. 2021.
[9] Chu et al. 2021.
[10] Khan et al. 2021.
[11] Ludl et al. 2020.
[12] Wu et al. 2020.
[13] Bai–Cheng 2020.

Figure 9 presents the share of each application, which employed DL in social information. Based on Figure 9, prediction (about 44%) followed by detection (about 31%) were the areas employing DL the most for social information applications. In Miao–Yang (2022), graph neural network (GNN) was employed in collaborative signals detection. In Daneshvar et al. (2022) convolutional neural network (CNN) and LSTM were employed for the detection of situations for social hybrid recommendation. In Zhang et al. (2022) some GNN techniques were employed to predict factors affecting social recommendation. In Zamboni et al. (2022) CNN and recurrent neural networks (RNN) were employed to develop a platform for the prediction of pedestrian trajectory. In Masson–Isik (2021) CNN was employed to predict social interaction perceptions. In Chopra–Kaur (2021) CNN was employed to develop a platform for IoT-based group size prediction. In Bi et al. (2021) GNN was employed to identify situations for proposing the social recommendation system.

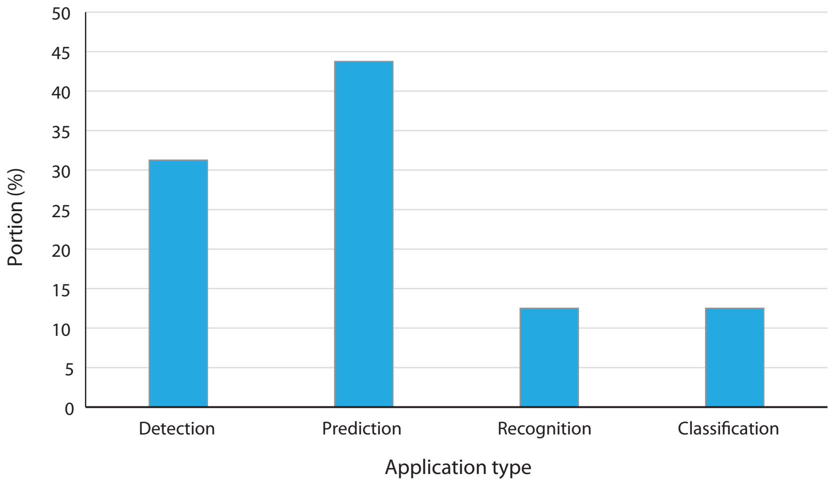


Figure 9: The statistical report of the application type
Source: compiled by the authors

Table 4 presents the evaluation results and the advantages of each DL technique in each application, separately.

Table 4: The evaluation results and the advantages of each DL technique

Ref.	Evaluation criteria		Advantages
Miao–Yang 2022	NA	NA	Captures reliable information
Daneshvar–Ravanmehr 2022	NA	NA	Using DL improved the effectiveness of the model
Zhang et al. 2022	Precision	0.99	The proposed technique was successfully able to cope with the task
Zamboni et al. 2022	NA	NA	More advanced techniques were proposed
Masson–Isik 2021	Performance score	0.48	Reduces the gap between the real world and the experimental approach
Zhang et al. 2021	Kappa index	0.61	The model can successfully be employed to investigate the historical POI data
	Accuracy	0.84	
Cui et al. 2021	Accuracy	0.9	The method provided a real time classification
Chu et al. 2021	AUC	0.91	Provides an automated detection platform for patients
	Accuracy	0.875	
	Sensitivity	0.88	
	Specificity	0.87	
Chopra–Kaur 2021	RMSE	1.18	Issued labels to improve the estimation performance
Khan et al. 2021	Accuracy	0.95	The platform ensured the reliability of real-time depression analysis
Bi et al. 2021	MAE	0.71	Provided a platform to improve the quality of recommendations
	RMSE	0.97	
Ludl et al. 2020	Accuracy	0.98	The proposed technique was successfully able to handle the task
Wu et al. 2020	Accuracy	0.893	The platform enabled efficient placement decisions to be taken in a real-time task
Cong 2020	MAE	0.71	The proposed technique has a suitable application effect on TV films and programs
Diaz et al. 2021	AUC ResNet3D-34	0.81	The proposed platform allowed real-time detection
	AUC ResNet3D-18	0.79	
Bai–Cheng 2020	Accuracy	0.96	Provided valid and accurate outputs in real experiments
	Precision	0.95	
	Recall	0.95	

Source: compiled by the authors

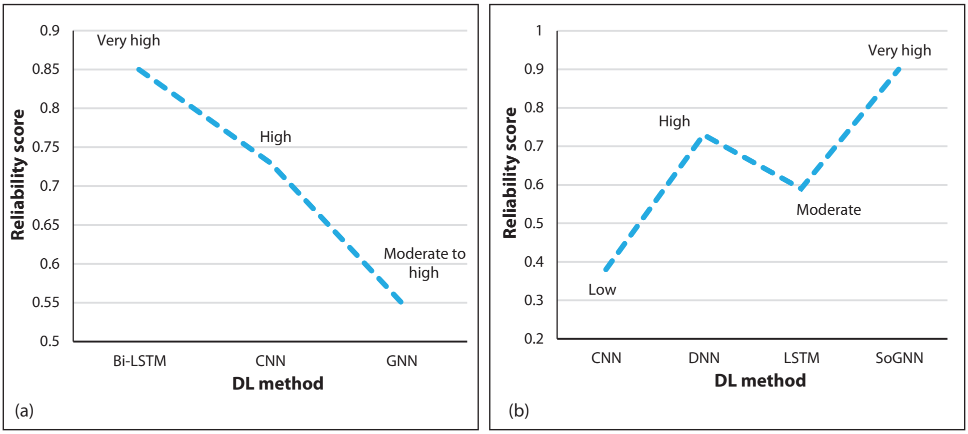
According to Table 4, some of the cases did not provide evaluation criteria. There are several reasons for this. In some cases, the evaluations were performed by graphical comparisons. In some cases, the study was conducted in order to develop a system without an evaluation step and in some cases, the full text was not available. In general, most of the cases employing DL techniques were evaluated as promising analytical tools to help address the research problem. Figure 10 presents the general evaluation of each DL in each application based on the strategy employed in our previous study.[14] We performed a relative reliability analysis by normalising accuracy, precision, and recall values (Eq. 1):

$$Z_N = \frac{g(Accuracy, Precision, Recall) - Z_{min}}{Z_{max} - Z_{min}} \tag{1}$$

where Z_N refers to the normalised reliability point, and Z_{min} and Z_{max} are the parameters (depending on the specific metric reported) employed for the limitations of the scores to provide scores between 0 and 1. For better interpretation, we further separated Z values into four categories:

Low if $0 \leq Z_N < 0.25$
Moderate if $0.25 \leq Z_N < 0.5$
High if $0.5 \leq Z_N < 0.75$
Very high $0.75 \leq Z_N \leq 1$

Figure 10 presents the reliability of the DL methods used in social information. The x-axis lists the DL methods, and the y-axis presents the reliability score, which is computed using Equation 1.



[14] Band et al. 2022.

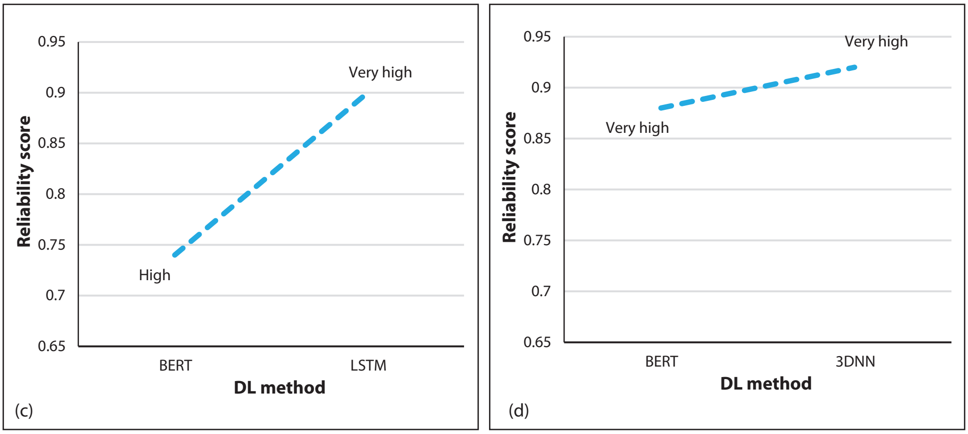


Figure 10: Reliability score for a) detection, b) prediction, c) recognition, and d) classification
Source: compiled by the authors

Bi-LSTM and LSTM displayed very high reliability scores for detection and recognition purposes, respectively, while for prediction, LSTM had a moderate reliability score. CNN achieved high reliability for detection purposes, while it exhibited a low-reliability score for prediction. GNNs achieved moderate to high reliability scores for detection purposes, while some GNNs provided very high reliability scores for prediction. BERT produced high and very high reliability scores for recognition and classification purposes, respectively. It can be observed that the reliability score depends on the application type.

Social network

Table 5 presents the information about the notable studies that employed DL in different applications connected to the topic of social networks. The nature of the content of Table 5 is similar to Table 3. Table 5 indicates some limitations of the studies developed. The phrase "NA" refers to non-available content.

Table 5: Notable DL-based studies for social network analysis

Ref.	Year	Description	Model parameters	Method	Analysing data source	Evaluation criteria	Application	Keyword
Zhao–Liu 2020	2021	To enhance the overall utility of vehicle drivers	Social-aware incentive mechanism	DRL	Model data	Average utility, extrinsic utility, intrinsic utility	Optimisation	Vehicular crowdsensing
Cowen et al. 2021	2021	Investigating human facial expressions with specific social contexts in different cultures for adaptive responses to different emotions	7 × 7 feature map comprising 1,024 channels, 7 × 7 average pooling layer, 1,024-dimensional vector	DNN	Contexts in 6 million videos from 144 countries	Accuracy and std. deviation	Classification	Human facial expressions, naturalistic social contexts
Xingxing et al. 2021	2021	Point of interest recommendation systems	NA	GNN	Feature extraction from graphs	NA	Modeling	Point of interest, nonlinear interaction
Ivanenko et al. 2021	2021	To classify sex and strain	NA	DNN	Recorded dataset	Accuracy	Classification	Ultrasonic vocalisations

Source: compiled by the authors

As is clear from Table 5, in social networks, the number of studies reported, which employed DL technique is low, and this entails some limitations for analysing and evaluating the application of DL techniques in this field. According to the data presented in Table 5, classification is the main application of DL for researching social networks. For this purpose, accuracy was employed as the criterion for the evaluation of DL techniques in these applications. Zhao and Liu (2020) employed deep reinforcement learning (DRL) for optimisation and to enhance the overall utility of vehicle drivers. Cowen et al. (2021) employed DNN to classify human facial expressions with specific social contexts in different cultures for adaptive responses to different emotions. Xingxing et al. (2021) developed a recommendation system for modelling purposes using GNN. Ivanenko et al.

(2020) also developed a classification system for selecting sex and strain. Table 6 presents the numerical findings and the advantages of each model in the social network.

Table 6: The evaluation results and the advantages of each DL technique

Ref.	Results		Advantages
Zhao–Liu 2020	Average utility	0.8–2	Optimal sensing and solution strategy
	Extrinsic utility	0.8–2	
	Intrinsic utility	0.1–1.6	
Cowen et al. 2021	Natural faces	0.84	Neutral classification in terms of region and gender
	Native origin	0.87	
Xingxing et al. 2021	NA	NA	Improved data sparsity and cold start in recommendations
Ivanenko et al. 2020	Accuracy DNN	0.77	To achieve above-chance classification
	Accuracy SVM	0.56	
	Accuracy LR	0.51	

Source: compiled by the authors

By employing Equation 1, it can be concluded that DNN achieved a moderate reliability score for classification purposes. Also, for optimisation purposes regarding social network data, DRL provided a high optimisation capability.

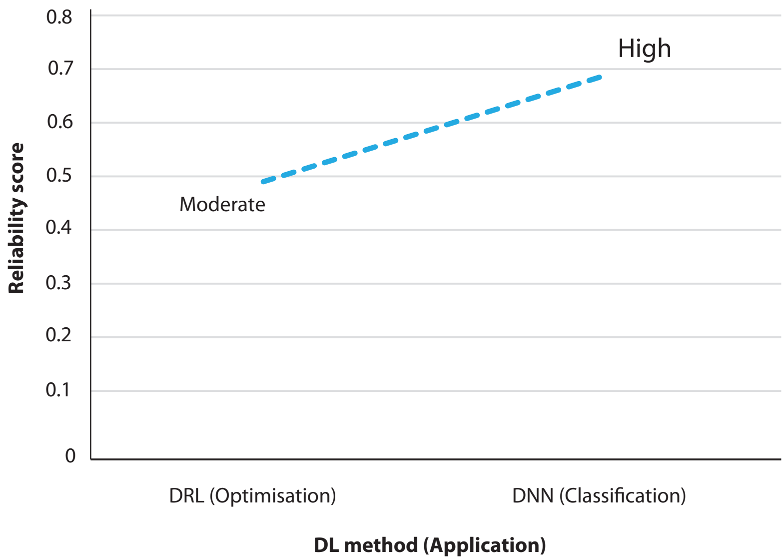


Figure 11: Reliability score for DRL and DNN
Source: compiled by the authors

Social development

Table 7 presents information about the notable studies that employed DL in different applications connected to social development. Table 7 presents the hot points of the studies developed. The phrase "NA" refers to non-available content. However, the main limitation related to this field is the lack of enough studies to investigate.

Table 7: Notable DL-based studies for social development

Ref.	Year	Description	Model character	Method	Analysing data source	Evaluation criteria	Application	Keyword
Kim et al. 2021	2021	To better understand biases in DL models to identify school development	ResNet18	DNN	3,424 satellite imagery	Accuracy	Identification	International development
Ren et al. 2018	2021	To model the interaction between objects and model every trajectory's moving pattern	NA	RNN	NA	NA	Prediction	Human trajectory

Source: compiled by the authors

Table 7 illustrates how studies on social networks applied DL for identification and prediction purposes. Kim et al. (2021) proposed a DNN-based technique to investigate school development. Moreover, Ren et al. (2018) presented an RNN-based modelling technique to evaluate the interaction between objects and model every trajectory's moving pattern. Table 8 presents the main results and criteria for evaluating the performance of the DL techniques. Using Equation 1, it can be observed that the reliability score of the DNN for identification purposes is evaluated as moderate.

Table 8: The evaluation results and the advantages of each DL technique

Ref.	Results		Advantages
Kim et al. 2021	Accuracy	0.84	Improve the bias detection framework
Ren et al. 2018	NA	NA	The proposed technique successfully copes with the task

Source: compiled by the authors

Social media

Table 9 presents the notable DL-based studies on the subject of social media. As Table 9 shows, DL in social media has been employed for detection,[15] recognition,[16] and prediction[17] purposes.

Table 9: Notable DL-based studies for social media

Ref.	Year	Description	Model character	Method	Analysing data source	Evaluation criteria	Application	Keyword
Tirdad et al. 2021	2021	For sentiment analysis of medically related texts	Filter size 205 for LSTM	CNN, LSTM, BLSTM	Concussion tweets – 2018 dataset	F1-score, precision, recall	Detection	Sentiment analysis, concussion
Li–Goldwasser 2021	2021	To analyse the text model using signals from the rich social and linguistic context	Stopping patience is equal to 10	Bidirectional encoder nsformers	Allsides and SemEval news dataset	Accuracy	Recognition	Political perspective
Khaefi et al. 2018	2018	To forecast air quality	VGG-16	CNN	Photos shared on social media	Accuracy	Prediction	Haze severity inference

Source: compiled by the authors

To evaluate the use of DL in social media, we employed data presented in Table 10 and calculated the reliability score by Equation 1. Figure 12 presents the reliability scores.

15 Tirdad et al. 2021.
16 Li–Goldwasser 2021.
17 Khaefi et al. 2018.

Table 10: The evaluation results and the advantages of each DL technique

Ref.	Results		Advantages
Tirdad et al. 2021	CNN F1-score	0.621	Provides an understanding of the culture around concussion through sentiment analysis
	CNN Accuracy	0.617	
	LSTM F1-score	0.613	
	LSTM Accuracy	0.612	
	BLSTM F1-score	0.607	
	BLSTM Accuracy	0.622	
Li–Goldwasser 2021	CNN Accuracy	0.84	Pre-training provided an effective improvement in the accuracy of the model
	BERT Accuracy	0.84	
	Ensemble Accuracy	0.86	
Khaefi et al. 2018	Accuracy	0.8724	Using social media datasets improves real-time forecasting of property

Source: compiled by the authors

Figure 12 illustrates that the reliability score of CNN for detection is evaluated as moderate but for prediction, CNN achieved a very high score. For recognition purposes, the Ensemble technique produced a very high score, while BERT and CNN provided High scores. In detection, BLSTM improved reliability in comparison with LSTM and CNN with a score from Moderate to High. In general, it appears that the reliability score of prediction and recognition applications is higher than the score for detection applications.

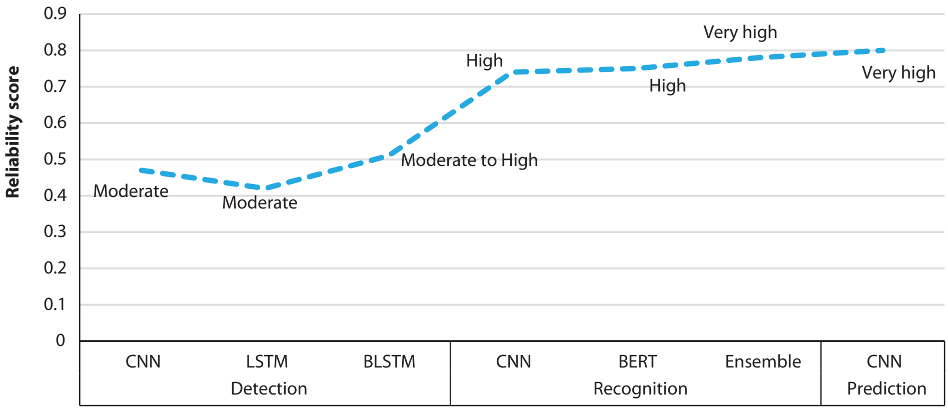


Figure 12: The reliability score
Source: compiled by the authors

Studies

Social environments

Table 11 presents the notable DL-based studies on social environments. Figure 13 presents the statistical report on the share of applications of DL. As can be seen in Figure 13, Detection represented the highest proportion (30%) in comparison with other applications. It can be asserted that, in the field of social environment, detection is the main problem that required DL-based techniques. Figure 13 presents the statistical report on the evaluation criteria employed in the social environment.

Table 11: Notable DL-based studies for social environments

Ref.	Year	Description	Model character	Method	Analysing data source	Evaluation criteria	Application	Keyword
Tsiktsiris et al. 2020	2020	Real-time abnormal event for security improvement	NA	LSTM	3 hidden layers, size (32 × 64), the rectified linear unit (ReLU) activation function	Accuracy, F1-score, recall and precision	Detection	Crimes detection
Liu–Zhang 2020	2019	To evaluate mental health courses	NA	CNN, DBN	Data from colleges and universities	NA	Optimisation	Evaluation feedback
Shukla et al. 2019	2019	Sharing a common house space with humans	Four-layered convolutional with batch normalisation activation ELU	RNN-LSTM, CNN	Combination of public datasets	Accuracy, F1-score, recall and precision	Recognition	Humanoid robots
Thang et al. 2018	2019	Source location and type classification of noise	SB-CNN, VGG-16, VGG-16-PRE	CNN	SNU-B36-50	Accuracy	Classification	Noise between floors

Ref.	Year	Description	Model character	Method	Analysing data source	Evaluation criteria	Application	Keyword
Feng et al. 2018	2018	To recognise multistage and elastic spam in social media	Convolutional layer of 128 word vector with Max-over-time Pooling method	CNN	Sina Weibo dataset	Accuracy	Detection	Mobile social networks
Jaiswal et al. 2018	2018	To evaluate the command direction by a finger pointing gesture	Kernel size from 3 x 3 to 5 x 5 in each of the units with rectified linear unit (ReLU) activation function	CNN	24,000 images	MSE	Estimation	Gesture based communication
Luo–Hsieh 2017	2017	To evaluate situational context perception	The first convolutional layer convolves 32 filters of 5 x 5 with stride 1 followed by rectifier linear unit (ReLU)	LSTM	Real-world image data	Accuracy	Detection	Human social environments

Source: compiled by the authors

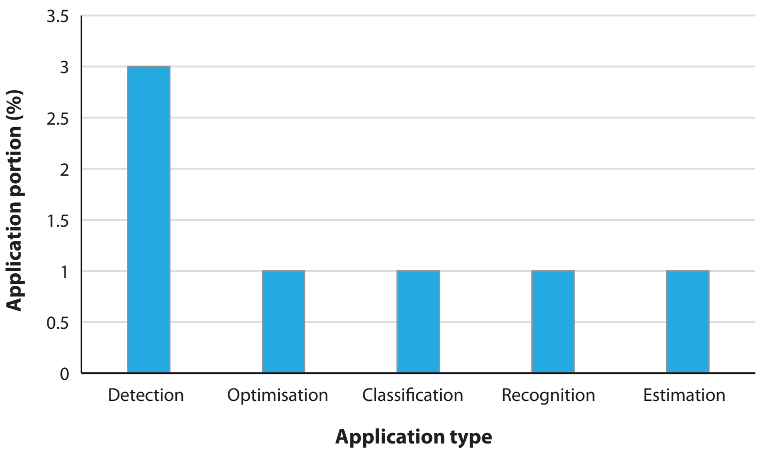


Figure 13: The statistical report of the application type
Source: compiled by the authors

Figure 14 presents evidence supporting the claim that the Accuracy criteria is the most frequently used evaluation criteria for the application of DL in Social environments. Table 12 presents the main findings and advantages of the proposed methods and procedures for each study, separately.

Table 12: The evaluation results and the advantages of each DL technique

Ref.	Results		Advantages
Tsiktsiris et al. 2020	Accuracy	0.996	The proposed method improved timely detection of petty crimes incidents
	Precision	0.98	
	Recall	0.98	
	F1-score	0.98	
Liu–Zhang 2020	NA	NA	Continuously explore in the shallow information
Shukla et al. 2019	Gesture accuracy	0.98	The proposed technique provided real-time detection capability
	Speech accuracy	0.913	
Thang et al. 2018	SB-CNN	0.674	Pre-training provides a higher classification performance
	VGG-16	0.707	
	VGG-16-PREtrained	0.96	
Feng et al. 2018	Accuracy	0.913	The proposed platform improved the utilisation rate of computing resources and realised real-time application
Jaiswal et al. 2018	MSE	< 0.0001	The proposed technique was able to implement humanoid robots in real time
Luo–Hsieh 2017	Encoded image + HOG	0.947	The proposed platform improved the identification of assistance via taking spatio-temporal factor into consideration
	Encoded image + optical flow	0.887	
	Optical flow + HOG	0.981	

Source: compiled by the authors

Accordingly, Figure 15 was prepared to present the reliability score (calculated from Equation 1). Based on Figure 15, it can be stated that CNN plays different roles for different applications. CNN achieved a very high reliability score for detection, while exhibiting moderate and high scores for estimation and classification purposes. Also, RNN-LSTM achieved very high reliability scores for recognition and LSTM for detection purposes.

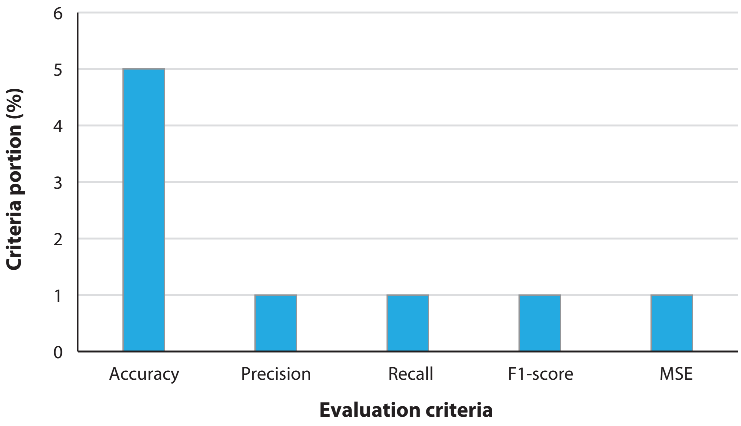


Figure 14: Statistical report of the evaluation criteria
Source: compiled by the authors

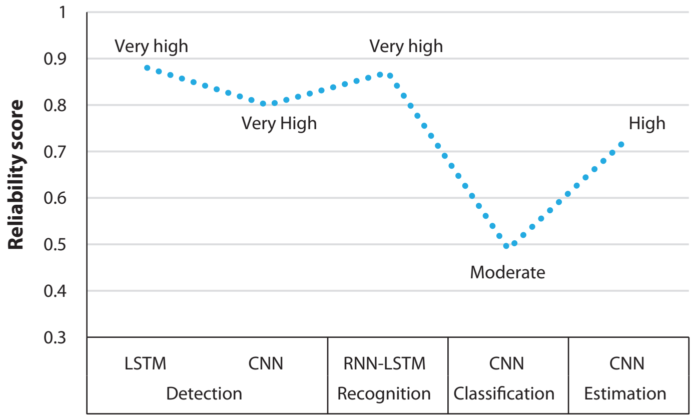


Figure 15: The reliability score
Source: compiled by the authors

Social risk

Table 13 presents several notable DL-based studies on social risk applications. As reported in Table 13, DL has been employed for detection, prediction, and forecasting purposes of the social risk. Choi et al. (2022) employed BERT to "claim a sentence of a rumor" [*sic*] using 7,403 claims from fact-checking sites and evaluated the model using the area under the curve (AUC) and accuracy criteria. Liu (2021) employed a classification and regression tree (CART) and CNN to forecast risk information of the community in the presence of the community public information. The evaluations were performed by correlation coefficient and mean square error (MSE) values. Gao et al. (2019) employed spatial incomplete multi-task deep learning to predict Spatio-Temporal Event Subtype and evaluated the model by AUC factor. In general, it can be said that accuracy and AUC have been frequently used for the evaluation of DL techniques in social risk.

Table 13: Notable DL-based studies for social risk

Ref.	Year	Description	Model character	Method	Analysing data source	Evaluation criteria	Application	Keyword
Choi et al. 2022	2022	"To claim sentence of a rumor" *[sic]*	Twelve fully connected layers	BERT	7,403 claims from fact-checking sites	AUC and accuracy	Detection	Rumor spread
Liu 2021	2021	To forecast risk information of the community	NA	CART and CNN	Community public information	CC, MSE	Prediction	Public service information
Gao et al. 2019	2019	To predict Spatio-Temporal Event Subtype	The hidden representation learned by the shared hidden layers	Spatial Incomplete Multi-task Deep learning (SIMDL)	NA	AUC	Forecasting	Subtypes

Source: compiled by the authors

Table 14 presents the evaluation results and the advantages of each DL technique. Figure 16 shows the reliability score calculated by Equation 1.

Table 14: The evaluation results and the advantages of each DL technique

Ref.	Results		Advantages
Choi et al. 2022	AUC	0.7	The pre-trained model can successfully deal with a wide range of applications
	Accuracy	0.72	
Liu 2021	CC, CART	0.862	DL provided better system reliability
	MSE, CART	0.743	
	CC, CNN	0.925	
	MSE, CNN	0.855	
Gao et al. 2019	AUC	0.81	The proposed technique has been successfully coped with the task

Source: compiled by the authors

According to Figure 16, CNN for prediction achieved a very high reliability score, while CART provided high reliability for prediction. Furthermore, SIMDL provided high reliability for forecasting applications. Moderate reliability was achieved by BERT for detection purposes.

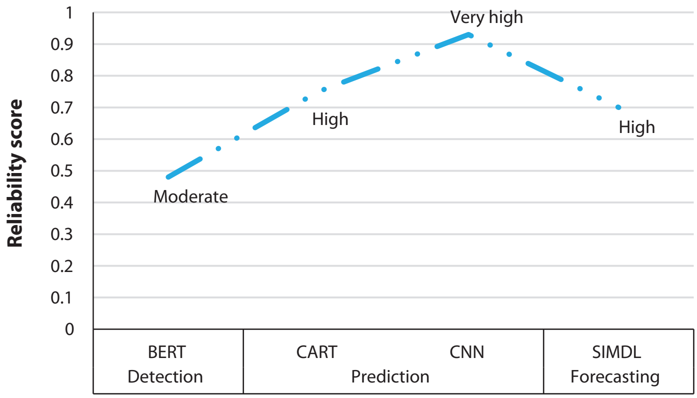


Figure 16: The reliability score
Source: compiled by the authors

Social health

Table 15 presents the notable DL-based studies on topics relating to social health. Figure 17 presents information about the evaluation criteria employed for evaluating DL techniques when applied in investigations relating to social health.

Table 15: Notable DL-based studies for social health

Ref.	Year	Description	Model character	Method	Analysing data source	Evaluation criteria	Application	Keyword
Zheng et al. 2019	2020	To handle the clinical assessment and treatment planning	Local features alone and global features alone	CNN	300 ms background activity	Accuracy, precision, sensitivity, specificity, AUC, F1-score	Detection	Spike detection

Studies

Ref.	Year	Description	Model character	Method	Analysing data source	Evaluation criteria	Application	Keyword
Xiao et al. 2020	2020	To recognise workers' wearing masks	VGG-19	CNN	3,000 mask images	Precision and recall	Detection	Wearing masks
Zhao et al. 2020	2020	To develop a visual food recognition platform	JDNet	CNN	UECFood256 and Food-101 datasets	Accuracy	Recognition	Mobile visual food
Meng et al. 2020	2020	To evaluate the physical and mental health of the elderly	NA	DNN	Street view images	Accuracy	Detection	Elderly health

Source: compiled by the authors

Figure 17 indicates accuracy provided the highest application portion (about 42%) for evaluating the DL in social health.

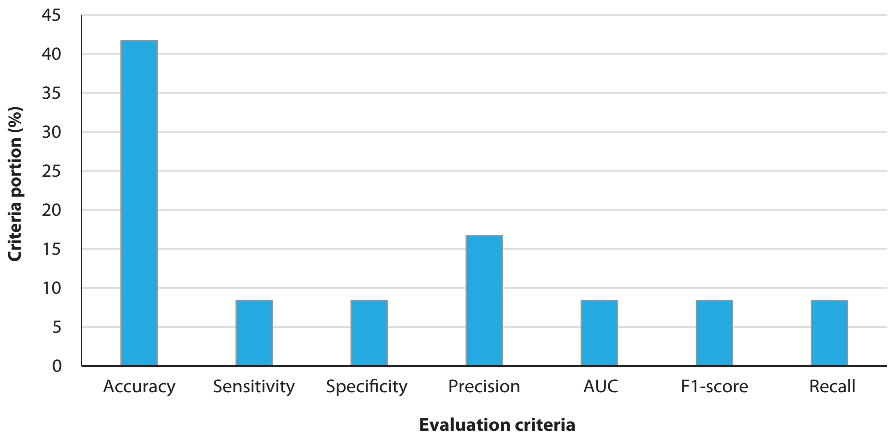


Figure 17: Statistical report of the evaluation criteria
Source: compiled by the authors

Table 16 presents the results and advantages of DL techniques used in studies on social health. Figure 17 was prepared by calculating the reliability score using Equation 1.

Table 16: The evaluation results and the advantages of each DL technique

Ref.	Results		Advantages
Zheng et al. 2019	Accuracy	0.99	General representation of epileptic spikes was successfully identified using the DL technique
	Precision	0.99	
	Sensitivity	0.99	
	Specificity	0.99	
	AUC	0.99	
	F1-score	0.99	
Xiao et al. 2020	Precision	0.97	The proposed technique provided a considerable improvement in reliability
	Recall	0.96	
Zhao et al. 2020	Accuracy UECfood	0.84	The proposed technique achieved high food recognition performance on mobile platforms
	Accuracy Food-101	0.91	
Meng et al. 2020	Accuracy	0.84	The obtained results provided practical significance for city managers and designers

Source: compiled by the authors

According to Figure 17, CNN provided very high reliability for detection purposes while CNN provided high reliability for recognition. In addition, DNN attained moderate and high reliability for detection and estimation purposes.

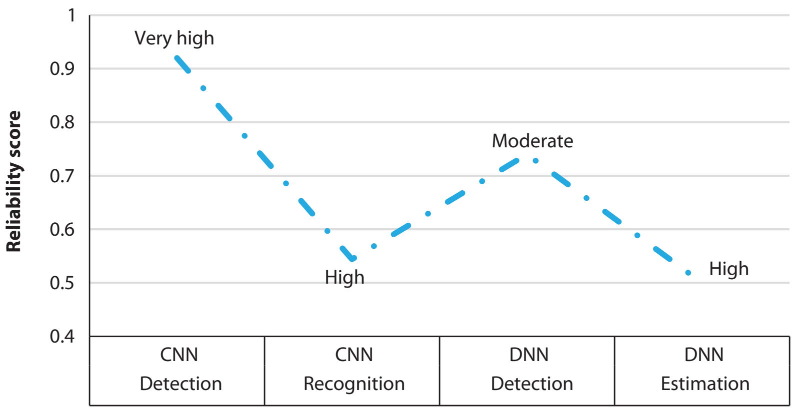


Figure 18: The reliability score
Source: compiled by the authors

Studies

Social conflict

Table 17 presents notable DL-based studies related to social conflict. Ma et al. (2022) employed LSTM to estimate pedestrians' trajectories to model crowds hierarchically. The evaluations were conducted by graphical analysis. Hana et al. (2020) employed CNN for the classification of the hate data in a database of Twitter posts. Choi et al. (2018) employed a pre-trained CNN technique to propose a classification platform. According to the analytical results, accuracy is the most frequently used evaluation criteria for evaluating DL in social conflict.

Table 17: Notable DL-based studies for social conflict

Ref.	Year	Description	Model character	Method	Analysing data source	Evaluation criteria	Application
Ma et al. 2022	2022	A conflict-avoiding technique to estimate pedestrians' trajectories to model a crowd hierarchically	RNN	LSTM	BIWI and UCY public dataset	Graphical analysis	Prediction
Hana et al. 2020	2020	To classify the hate speech in social media	6 layers, 768 hidden, 12 heads, and 134M parameters	CNN	Tweeter data	Accuracy	Classfication
Choi et al. 2018	2018	To propose a classification platform	VGG-16-PRE	Pretrained CNN	SNU-B36-50 dataset	Accuracy	Classfication

Source: compiled by the authors

Table 18 presents the results and advantages of the DL techniques employed. It is clear, however, that there is a lack of the evaluation criteria for further analysis. This can be considered the main limitation of DL-based studies on social conflict. By calculating the reliability score (using Equation 1), it can be said that CNN and pre-trained CNN provided significant differences in reliability scores (high and very high reliability scores, respectively) for detection purposes.

Table 18: The evaluation results and the advantages of each DL technique

Ref.	Results		Advantages
Ma et al. 2022	NA	NA	Same time prediction of the span using a shorter observation period
Hana et al. 2020	Accuracy	0.64	CNN provided a low accuracy rate
Choi et al. 2018	Accuracy	0.96	Pre-training is a promising technique

Source: compiled by the authors

Social inequalities

Table 19 presents the notable DL-based studies on the topic of social inequality analysis. Palmer et al. (2021) employed CNN to automatically extract and classify unhealthy advertisements. The evaluations were conducted by referring to the precision, recall, and F1-score. Zhou et al. (2019) employed deep convolutional encoder-decoder to provide a framework for understanding street visual walkability. The evaluation was conducted by accuracy criteria.

Table 19: Notable DL-based studies for social inequalities

Ref.	Year	Description	Model character	Method	Analysing data source	Evaluation criteria	Application	Keyword
Palmer et al. 2021	2021	To automatically extract and classify unhealthy advertisements	Stochastic gradient descent to implement complex functions	CNN	Street-level images collected	Precision, recall and F1-score	Classification	Unhealthy advertisements
Zhou et al. 2019	2019	To provide a framework for understanding street visual walkability	SegNet	Deep convolutional encoder-decoder	Images with corresponding ground	Accuracy	Detection	Visual walkability

Source: compiled by the authors

Table 20 presents the evaluation metrics and advantages of the models. Accordingly, the reliability score was calculated by Equation 1 and presented in Figure 18.

Table 20: The evaluation results and the advantages of each DL technique

Ref.	Results		Advantages
Palmer et al. 2021	Precision	0.662	The platform provided identification areas for tackling social inequalities
	Recall	0.787	
	F1-score	0.718	
Zhou et al. 2019	Accuracy	0.785	The proposed platform can be extended to other unfeasible or challenging cases

Source: compiled by the authors

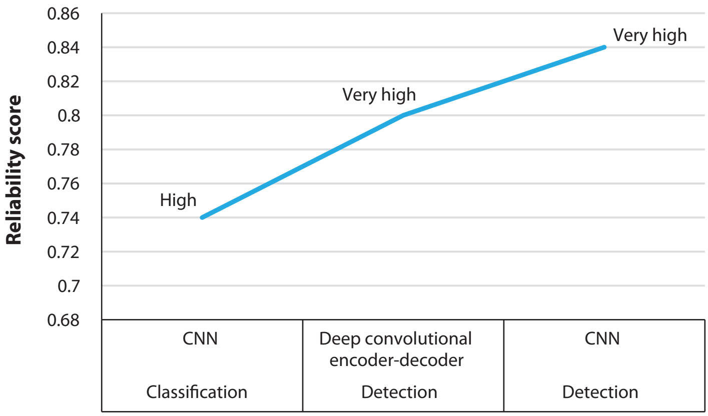


Figure 19: The reliability score
Source: compiled by the authors

According to Figure 19, CNN achieved very high and high reliability scores for Detection and Classification purposes, respectively. Moreover, the deep convolutional encoder-decoder achieved a very high reliability score for Detection purposes.

Other applications

We created a section entitled other applications for those applications, which do not include Social cooperation, Social movement, and Social technology. A limitation of these applications is that there is an insufficient number of such studies and analytical evaluation metrics. In addition, there was a lack of the analytical datasets for analysing Social cooperation, Social movement, and Social technology applications. These limitations hinder the evaluation prospects for these studies and make statistical analysis difficult. This is one of the main disadvantages of the following applications, and is known to be their main limitation. Limited studies have been performed on these applications. Ni and Zhang (2022) employed multi-graph gated graph convolution to develop a platform for spatial-temporal traffic flow prediction. Zhang (2018) proposed a platform of highly intelligent robots using the CNN technique. Dam and Turzo (2021) employed GRU-RNN for handling a Bangla social media dataset to estimate social movements. Ertugrul et al. (2019) employed LSTM to explore protest events along with the social and geographical contexts. Zhang and Pan (2019) employed CNN for image data and LSTM-RNN for text data to investigate social media activities. In these cases, the lack of enough information in the dataset presented or in analytical results or model description prevented us from obtaining sufficient information to categorise and present reliability scores for evaluating the DL techniques employed in the studies.

DISCUSSION

For evaluating DL methods, it is often essential to review a series of parameters, metrics and criteria provided in the results section of each article. Some articles used evaluation and comparative parameters for assessment. Others used visual and graphic methods to examine and compare DL methods. However, the success rate of these parameters in evaluating deep learning methods in different applications is a general and important question. This study seeks to fill this gap in the evaluation of DL methods by employing the most innovative methods possible. The performance of different methods in different applications was in the focus of the previous sections. However, it is also important to consider whether the presented method is able to provide useful results when applied to all databases, and this reliability must be independent of the database type. With this aim in mind, we used a feature selection method in order to select the most effective parameter in determining the accuracy and performance of a network and, based on this, to determine the most suitable policy for future study. In this technique, we employed the Relief feature selection method to choose the most effective parameters for DL evaluation from each study separately. Accordingly, we emphasised y = f(x1,x2,x3) where y refers to the DL reliability score, x1 refers to the evaluation criteria, x2 refers to the database dimension and the number of the dataset, input variable, and output variables and x3 refers to the application type. This technique may allow us to find the most effective variables related to DL performance in order to formulate the policies based on the selected variable. The use of this technique is the first time that has been employed in the present study for evaluating the DL techniques applied in the social sciences. This method considers a data set with n samples with properties of p. The algorithm starts with a weight vector (W) zero and is repeated m times. Each iteration considers the attribute vector (X) belonging to a random instance, and next to that, the attribute vector indicates the instance closest to X. Based on this, the parameters of the closest instance of the same class are near-hit and the nearest instance of the different class is near-miss.[18] Equation 2 shows the weight vector:

[18] Kira–Rendell 1992.

$$\text{Weight}_i = \text{Weight}_i - (X_i - \text{near-tar.})^2 + (X_i - \text{near-lo.})^2 \tag{2}$$

Accordingly, the weight of properties close to the class increases and decreases in reverse. After m is repeated, each weight vector element is normalised to m. This is called the vector of a relation vector. Relief can also be described as generalisable to polynomial classification by breaking down several binary problems.[19] The relief feature selection technique was applied by Python software. Table 21 presents the output of the relief feature selection for choosing the best factor affecting the reliability score of DL methods in social science.

Table 21: The results of relief feature selection technique

Ref.	Evaluation criteria	Database	Application	Ref.	Evaluation criteria	Database	Application
Cowen et al. 2021	**	*	*	Zamboni et al. 2022	NA	**	**
Xingxing et al. 2021	NA	**	*	Masson–Isik 2021	***	**	*
Ivanenko et al. 2020	**	*	***	Zheng et al. 2019	**	**	**
Kim et al. 2021	***	*	*	Cui et al. 2021	**	*	*
Ren et al. 2018	NA	**	**	Chu et al. 2021	***	**	**
Tirdad et al. 2021	***	**	*	Chopra–Kaur 2021	***	**	**
Li–Goldwasser 2021	***	**	**	Khan et al. 2021	***	**	*
Khaefi et al. 2018	**	**	**	Bi et al. 2021	***	**	**
Tsiktsiris et al. 2020	*	**	*	Ludl et al. 2020	***	**	**
Liu–Zhang 2020	NA	**	*	Wu et al. 2020	**	*	**
Shukla et al. 2019	**	**	*	Cong 2020	**	*	**
Thang et al. 2018	***	*	*	Diaz et al. 2021	***	***	**
Feng et al. 2018	**	**	*	Miao et al. 2022	***	*	*
Jaiswal et al. 2018	***	*	**	Daneshvar–Ravanmehr 2022	***	**	*
Luo–Hsieh 2017	**	*	*	Zhang et al. 2022	***	**	**
Choi et al. 2022	**	*	*	Ma et al. 2022	***	**	*
Gao et al. 2019.	**	**	*	Hana et al. 2020	***	***	**
Zheng et al. 2019	***	***	*	Choi et al. 2018	***	**	**
Xiao et al. 2020	**	***	**	Chikushi et al. 2020	***	**	**
Zhao et al. 2020	***	**	**	Palmer et al. 2021	***	*	*
Meng et al. 2020	***	*	*	Zhou et al. 2019	***	**	**
				Total score	Very High	Moderate	Moderate

Source: compiled by the authors

[19] Kira–Rendell 1992.

The results presented in Table 21 suggest that the most effective parameter of DL reliability is the evaluation criteria. The effect of database and application type is moderate. Accordingly, it can be considered that the best criteria for evaluating the DL techniques are evaluation criteria values. Based on this conclusion, some limitations can be identified in the studies that were surveyed. One of their main limitations is the lack of reporting evaluation criteria values in the evaluation phase. Some studies did not calculate these parameters to examine the model employed. Other limitations include the lack of reporting on the structure and architecture of the models and networks used by some of the studies, which deviate from the descriptive nature of the model and which do not allow the researcher to recommend policies based on these models. Also, some articles failed to provide the studied data and its sources, which can be a deterrent to further studies. This requires a proper policy when selecting and preparing the articles that employed ML and DL techniques for different applications, in order to prevent similar limitations in future.

CONCLUSIONS

This study reviews and presents the performance of DL methods in the social sciences. It finds that accuracy and AUC are the key metrics for evaluating DL techniques in social information. LSTM is reliable for detection and recognition and also popular for prediction. In social networks, the limited number of studies expressed the evaluation, with DNN being moderately reliable for classification and DRL capable for optimisation. Social media analysis rates CNN as moderately reliable for detection and very high for prediction, with Ensemble techniques, BERT, and CNN scoring high for recognition. In the social environment, CNN is very reliable for detection and moderately to highly reliable for estimation and classification. For social risk, CNN shows very high prediction reliability, and CART shows high reliability. In social health, CNN is very reliable for detection and recognition, while DNN is moderately to highly reliable for detection and estimation. In social conflict, evaluation criteria are lacking, limiting analysis, but CNN and pre-trained CNN show high to very high reliability for detection. For social inequalities, CNN scores very high for detection and high for classification, with deep convolutional encoder-decoder also scoring very high for detection. Other applications face limitations due to insufficient studies and metrics for comparison. The review emphasises the importance of transparent evaluation criteria, model structure, and architecture to ensure reproducibility and advancement of DL research in social sciences.

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Sina Ardabili is a Research Fellow at the Ludovika University of Public Service Institute of the Information Society. He had been among the top 2% scientists based on the Stanford University study since 2021. His research interest include smart systems and artificial intelligence. His research during PhD studies has been on the application of artificial intelligence systems and smart systems. He has several highly cited review papers on the application of machine learning and deep learning systems. His latest book is *Autonomous Agricultural Vehicles: Concepts, Principles, Components, and Development Guidelines.* CRC Press, 2023.

Amir Mosavi is a Research Fellow at the Ludovika University of Public Service Institute of the Information Society. His research interests include applied artificial intelligence. He was an Alexander von Humboldt fellow and the recipient of the Marie Skłodowska-Curie and the European Research Consortium for Informatics and Mathematics fellowships.

Csaba Makó, Professor, Institute of the Information Society, Ludovika University of Public Service, Budapest, Hungary. Research interest: international comparative analysis of the social – economic institutions/regulations of the game-changing technological (digitisation, smart automatisation, artificial intelligence and algorithmic management) and organisational innovations. Special focus of his research interest is related with quality of work, skills formation and employment status. Latest major project: *"Democracy at Work Through Transparent and Inclusive Algorithmic Management"* (INCODING), EU, 2021–2024.

Péter Sasvári, PhD, Associate Professor (2013) of the Department of Public Management and Information Technology, Faculty of Public Governance and International Studies, Ludovika University of Public Service, Budapest, Hungary (Part time: University of Miskolc, Hungary). He obtained his doctoral thesis with the best receivable mark, "summa cum laude". The title of his dissertation was *The Development of Information and Communication Technology: An Empirical Study.* Sasvári is the supervisor of 4 PhD students' theses, has supervised more than 150 bachelor's and master's theses; he is a member of the public body at the Hungarian Academy of Sciences. He is the author of more than 90 international publications, serves as the associate editor for 3 international journals. Scientometrics has been in the focus of his researches, recently. With the co-operation of some local universities, he has conducted a primary research among small and medium-sized enterprises in Austria, Bosnia-Herzegovina, the Czech Republic, Croatia, Poland, Portugal, Hungary, Germany, Italy, Spain and Slovakia.