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Article

ML AND DL CROSS-DOMAIN ANALYSIS ASSESSING THEIR INFLUENCE IN VARIOUS DOMAINS

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Abstract: Machine Learning (ML) and Deep Learning (DL) technologies are indispensable in the fields of solving complex problems across different application areas. In this study, the authors compare cross domain use of ML and DL algorithms across three industry sectors—healthcare, natural language processing (NLP), and network security. The pre-processing of publicly available benchmark datasets was performed on the data using Data Cleaning, Normalization, Feature Selection and Text Preprocessing methods. A total of 4 ML algorithms (Random Forest, XGBoost, LightGBM and CatBoost) and 4 DL algorithms (CNN, LSTM, GRU and Transformer) were tested on classification accuracy. The outputs show that the deep learning models generally outperform the machine learning algorithms with the highest accuracy in all the domains being achieved by Transformer and XGBoost being the best-performing machine learning algorithm. This research points out advantages and disadvantages of both strategies, and guides selection of appropriate algorithms in a variety of real-world applications.
Keywords: Healthcare, Natural Language Processing, Financial Services, Network Security

1. INTRODUCTION

Machine Learning (ML) is one of the most powerful fields of Artificial Intelligence (AI) that allows computer systems to learn from data and make intelligent decisions without having to be explicitly programmed. ML can leverage these statistical models and computational algorithms to analyse vast amounts of structured and unstructured data and discover signals of significance, forecast future trends and make decisions that are complex. Machine learning is a core technology across various industries, including healthcare, finance, agriculture, cybersecurity, education, and manufacturing, due to its iterative nature and capacity to learn continually from experience. Its widespread use has made a substantial impact on the operational efficiency, predictive capabilities, and intelligent automation of many real-world applications.

There are several machine learning techniques, they are broadly categorized into: Supervised, Unsupervised and Reinforcement learning techniques. Supervised learning uses a labeled training set to build predictive models for classification and regression, whereas unsupervised learning extracts hidden structures, clusters or associations from unlabeled data. RL is a method that allows the intelligent agent to learn optimal actions by performing interactions with its environment and maximize cumulative rewards by trial and error. These learning paradigms offer flexible, versatility to solve a variety of analytical and predictive tasks as a function of the type of available data and application needs. Deep Learning (DL), a niche of machine learning, has transformed AI by using multi-layered artificial neural networks to simultaneously process vast amounts of data and automatically learn complex features from them. Unlike traditional machine learning techniques which typically require handcrafting features, deep learning algorithms learn hierarchical representations directly from raw data and achieve better results in image, speech, text, and video applications.

The capabilities of intelligent systems have greatly advanced in solving highly complex problems using advanced architectures like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Transformer based models. Deep learning has several benefits over the traditional machine learning approach in the context of a high-dimensional and complex dataset. It automatically extracts features, decreases the reliance on handcrafted features, and efficiently learns the nonlinear relationships between features. For these types of applications including medical image analysis, natural language processing, speech recognition and autonomous systems, deep learning models typically offer higher predictive accuracy. In addition, the vast amount of available data, powerful graphics processing units (GPUs), and cloud computing resources have enabled the rapid deployment and development of deep learning models in a wide range of industrial and research applications. Machine learning (ML) and deep learning (DL) are now being applied in a diverse range of areas.

In medicine, they aid in the identification of disease, the classification of medical images, risk assessment of patients, and customization of treatment. They are commonly applied in the field of financial services, such as fraud detection, credit scoring, risk evaluation, and algorithmic trading. In the field of NLP, they can be used for sentiment analysis, language translation, text summarisation, and conversational AI systems. In the realm of network security, intelligent models can be used for intrusion detection, malware classification, anomaly detection, and predicting cyberattacks. These are just a few examples, and the applications span various industries, highlighting the diverse ways in which ML and DL can be applied. With the development of machine learning and deep learning, their performance in various application fields is gradually becoming a concern.

The existing studies are mostly limited to a specific domain or a particular algorithm, which makes it hard to find the best technique for different data characteristics and problem size. The cross domain analysis is used to get a comprehensive understanding of the strengths and weaknesses, adaptability and generalization capabilities of various ML and DL algorithms in various real-world applications. Such comparison helps researchers and practitioners choose suitable models for domain specific problems, as well as discovering potential directions for building better, transferable, and scalable intelligent systems. Hence, the focus of this study is to provide a cross-domain analysis of machine learning and deep learning by exploring their impact and comparative performance across four sectors—healthcare, natural language processing, financial services, and network security.

2. LITERATURE REVIEW

Chen et al. (2024) assert that in this age of information overload, recommendation systems are crucial for identifying appealing items amidst the influx of online digital engagements and e-commerce. Numerous methodologies have been extensively utilised in recommendation systems; however, the cold-start and sparsity issues persist as significant obstacles. The cold-start dilemma arises when formulating suggestions for new users and goods without enough data. Sparsity denotes the issue of possessing many users and things yet experiencing few transactions or interactions. This article presents a new cross-domain recommendation model, Cross-Domain Evolution Learning Recommendation (CD-ELR), designed to convey information across various domains to address cold-start and sparsity challenges through the integration of matrix factorisation and recurrent neural networks. We provide an evolutionary framework to explain the fluctuations in user preferences across time. Moreover, various optimisation techniques have been devised to amalgamate the domain characteristics for accurate recommendations. Empirical findings indicate that CD-ELR surpasses current leading recommendation benchmarks. Ultimately, we perform experiments on various real-world datasets to illustrate the feasibility of the proposed CD-ELR.

Islam et al. (2026) The multi-faceted sentiment analysis of Bangla e-commerce evaluations poses difficulties due to the scarcity of annotated datasets, morphological intricacies, code-mixing occurrences, and domain shift challenges, impacting more than 300 million Bangla-speaking individuals. Current methodologies are deficient in explainability and the ability to generalise across domains, which are essential for effective implementation. We introduce BanglaSentNet, a transparent hybrid deep learning architecture. It incorporates LSTM, BiLSTM, GRU, and BanglaBERT via a theoretically substantiated dynamic weighted ensemble for multi-faceted sentiment classification. We present an extensive dataset comprising 8755 meticulously annotated Bangla product reviews, categorised into four dimensions—Quality, Service, Price, and Decoration—sourced from prominent Bangladeshi e-commerce platforms, exhibiting a confirmed inter-annotator agreement as per Fleiss'. Our methodology includes a cohesive explainability suite that merges SHAP-based feature attribution with attention mechanism visualisation to provide clear, interpretable insights. Experimental findings across five random seeds indicate that BanglaSentNet attains superior accuracy and F1-score, surpassing independent deep learning models by 3–7% and significantly exceeding standard machine learning methods. The components of explainability get an interpretability score of 9.4 out of 10, with an 87.6% consensus among 18 assessors. Cross-domain transfer learning trials demonstrate strong generalisation, achieving zero-shot performance that maintains 67–76% of the source domain's efficacy across several target domains. Few-shot learning using just 500–1000 samples attains 90–95% of the performance achieved with complete fine-tuning, hence considerably reducing annotation expenses. This study enhances ensemble learning techniques for under-resourced languages and offers practical, comprehensible solutions for Bangla e-commerce sites.

Zhu et al. (2023) assert that self-supervised learning (SSL) has emerged as a revolutionary method in machine learning, providing an effective way to use the enormous quantities of unlabelled data present in many fields. Through the establishment of auxiliary tasks that produce supervisory signals directly from the data, SSL reduces reliance on extensive labelled datasets, thus broadening the applicability of machine learning models. This manuscript offers an extensive examination of SSL methodologies utilised across various data forms, such as images, text, audio, and time-series information. We explore the foundational concepts that govern SSL, analyse prevalent techniques, and underscore particular algorithms suited for each category of data. Furthermore, we tackle the specific obstacles faced in implementing SSL across various domains and suggest prospective research avenues that may augment the efficacy and potential of SSL. This analysis highlights SSL's capacity to substantially enhance the creation of resilient, generalisable models adept at addressing intricate real-world challenges.

Kumar et al. (2025) Cross-domain sentiment analysis is a challenging endeavour due to variations in lexicon, shifts in context, and sentiment that is exclusive to certain domains. Traditional models are not recognised for their ability to generalise in unfamiliar domains, resulting in diminished accuracy and inconsistent transfer efficacy. This document introduces a deep learning architecture called SentXFormer, which is a transformer-oriented hybrid system that improves sentiment categorisation across diverse domains. SentXFormer uses the hybrid SentiConGRU-Net framework, including CNN and GRU layers with contextual embeddings from BERT, RoBERTa, and Domain-Adaptive BERT (DABERT). A domain adaptation component utilising adversarial training with a Gradient Reversal Layer (GRL) promotes the acquisition of domain-invariant representations. The research is conducted using 23,440 sentiment-tagged reviews from three publicly accessible datasets: Amazon (7,550 samples), Yelp (8,450 samples), and IMDB (7,440 samples). SentXFormer shown commendable performance in the specified domain, achieving accuracies of 98.7% (Amazon), 97.67% (Yelp), and 98.8% (IMDB). The model demonstrates stability regarding transferability across diverse domains, achieving an accuracy of 91–93% across all training and testing combinations. The comparative evaluation involving LSTM, CNN, GRU, and contemporary transformer-based adaptation models indicates that SentXFormer consistently outperforms existing baselines. The results demonstrate that SentXFormer is an effective, robust, and scalable instrument for sentiment analysis in diverse and practical customer review scenarios.

Chen et al. (2022) The ability of machine learning models to generalise knowledge to a "unseen" domain by learning from one or more "seen" domains is crucial for the development and implementation of machine learning applications in real-world scenarios. Domain Generalisation (DG) methodologies seek to augment the generalisation proficiency of machine learning models, wherein the acquired feature representation and the classifier are pivotal elements for enhancing generalisation and facilitating decision-making. In this manuscript, we introduce Discriminative Adversarial Domain Generalisation (DADG) using meta-learning for cross-domain validation. Our suggested framework aims to acquire a domain-invariant feature representation from source domains and extend it to previously unencountered domains. It comprises two primary elements that collaboratively construct a domain-generalized Deep Neural Network (DNN) model: (i) discriminative adversarial learning, which actively acquires a generalised feature representation across various “seen” domains, and (ii) meta-learning driven cross-domain validation, which emulates train/test domain shifts by employing meta-learning strategies during the training phase. The experimental assessment included a thorough comparison between our proposed method and other established methods across three benchmark datasets. The findings indicate that DADG consistently surpasses a robust baseline, DeepAll, and exceeds the performance of other current DG algorithms in the majority of evaluation scenarios.

Research Gap

Recent research shows that machine learning and deep learning have made great strides in applications across domains, but there are still some gaps in research. Instead of comparing the performance of different ML and DL algorithms in various application domains, Chen et al. (2022) concentrated on domain generalization with adversarial learning but mainly studied feature generalization. Zhu et al. (2023) discussed the possibility of utilizing self-supervised learning with the help of unlabeled data, but did not compare traditional machine learning with the latest deep learning models. However, Chen et al. (2024) tackled the cold-start and sparsity problems in cross-domain recommendation systems, but the proposed framework was only applicable to the recommendation task without wide applicability across different domains. While Kumar et al. (2025) and Islam et al. (2026) introduced sophisticated transformer models for sentiment analysis across different domains, their studies were limited to NLP tasks and failed to account for the performance in other critical sectors like healthcare, financial services, and network security. Moreover, the current research is mainly focused on the design of application-specific models or the improvement of an individual algorithm, while very few have attempted to make a comprehensive comparison of the state of the art in ML and DL algorithms using benchmark datasets from different fields of application. Thus, a systematic cross-domain comparative evaluation of the effectiveness of these advanced machine learning and deep learning algorithms for various real-world domains is warranted to find out their strengths, weaknesses and applicability.

3. OBJECTIVES OF THE STUDY

1. To study the applications of ML and DL in different domains.
2. To compare the performance of ML and DL algorithms.
3. To identify the advantages and limitations of ML and DL.
4. To evaluate the impact of ML and DL across various domains.

4. METHODOLOGY

The research employs a cross-domain comparative approach of Machine Learning (ML) and Deep Learning (DL) algorithms across four key application areas: healthcare, natural language processing (NLP), financial services, and network security. The study uses a comparative method to assess the applicability, efficiency and ability to predict the performance of complex ML and DL algorithms within specific areas. There are four main steps to this methodology: Data collection, Data processing, Model implementation and Model evaluation. Benchmark datasets in the public domain are gathered from various domains and subjected to suitable preprocessing techniques to enhance data quality of the datasets. The selected ML algorithms include Random Forest (RF), XGBoost, LightGBM, and CatBoost while DL algorithms include Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Transformer (BERT/ViT). All algorithms are tested for their classification accuracy for their effectiveness in various application fields.

i. Dataset

This study gathers benchmark datasets from four distinct areas such as healthcare, natural language processing (NLP), financial services and network security. This is used in the healthcare domain to classify Alzheimer's. The Sentiment140 Dataset, which consists of tweets to analyze sentiment, is used in the NLP domain. The financial services domain employs a Credit Card Fraud Detection Dataset for the purpose of detecting fraud and the network security domain employs a NSL-KDD for use in intrusion detection and classification of cyberattacks. The datasets chosen are commonly used in the machine learning community and are well suited for benchmarking algorithm performance in a variety of applications. All collected data is carefully checked for data quality, consistency and comparative analysis relevance.

ii. Preprocessing

In order to quality the data and boost the performance of the model, some preprocessing is done. For the healthcare dataset, missing values have been addressed using suitable imputation methods, and feature normalization and scaling ensures consistent data representation. To eliminate attributes that are redundant to help increase classification accuracy, feature selection techniques are used. The NLP data is preprocessed by removing stop words, stemming the text, lemmatizing, removing punctuation and special characters, and vectorizing the text to convert it into numbers that can be used for machine learning algorithms. Data cleaning, feature engineering, normalization, and Synthetic Minority Oversampling Technique (SMOTE) are used in the financial services dataset to overcome class imbalance and enhance the effectiveness of fraud detection. Normalization, feature extraction and anomaly detection are applied for the network security dataset, helping to detect malicious network activities effectively. Lastly, each data set is split into training and testing data sets in the ratio of 80:20 for dependable model evaluation.

iii. Algorithm Used

- **ML Algorithms**

Random Forest (RF)

Random Forest is an ensemble learning algorithm that builds a number of decision trees using a technique of bootstrap sampling and merges the results of these trees with majority voting. The algorithm resolves the problem of overfitting and increases the precision of the prediction by averaging the prediction results of separate decision trees. The mathematical description is:

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} h_i(x)$$

where $\hat{y}$is the predicted output, $N$is the total number of decision trees, and $h_i(x)$represents the prediction of the i^{th}decision tree.

XGBoost

XGBoost is an optimized gradient boosting algorithm in which the trees are added sequentially by solving an objective function which consists of the loss function and a regularization term. It enhances the prediction error and yet restrains the complexity of the model. The objective function is given by the equation

$$Obj^{(t)} = \sum_{i=1}^{n} \quad l(\hat{y}_i) + \Omega(f_t)$$

where

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \quad w_j^2$$

where $l$denotes the loss function, $T$is the number of leaf nodes, $w_j$represents the leaf weights, and $\gamma$and $\lambda$are regularization parameters.

LightGBM

LightGBM is a Histogram-based Gradient Boosting algorithm which adopts leaf-wise tree growth to boost the efficiency of computation. The prediction function is given by

$$\hat{y} = \sum_{k=1}^{K} \quad f_k(x)$$

where $K$is the number of decision trees and $f_k(x)$denotes the prediction of the k^{th}tree.

CatBoost

CatBoost is a gradient boosting algorithm for efficient processing of categorical features based on ordered boosting. The model for prediction is symbolized by

$$\hat{y} = \sum_{t=1}^{T} \quad \alpha_t h_t(x)$$

where $\alpha_t$is the weight assigned to the t^{th}tree, $h_t(x)$is the prediction of the t^{th}decision tree, and $T$is the total number of boosting iterations.

- **DL Algorithms**

Convolutional Neural Network (CNN)

CNN is a widely used deep learning network for image classification and feature extraction. It uses convolutional layers, pooling layers and fully connected layers, which learn hierarchical representations on their own from input data. The convolution operation is described by the following expression.

$$h_{ij} = f\left(\sum_{m} \sum_{n} \quad w_{mn} x_{i+m,j+n} + b\right)$$

where $h_{ij}$is the output feature map, w_{mn}denotes the convolution kernel, $x$represents the input feature map, $b$is the bias term, and $f$is the activation function.

Long Short-Term Memory (LSTM)

LSTM is a network architecture that is capable of modeling long-term dependencies in sequential data, using a memory cell and gating mechanism. The LSTM equations are given as

$$f_t = \sigma\left(W_f[x_t] + b_f\right)i_t = \sigma(W_i[x_t] + b_i)o_t = \sigma(W_o[x_t] + b_o)C_t = f_t \odot \quad C_{t-1} + i_t \odot \quad \tilde{C}_t h_t = o_t \odot \quad tanh(C_t)$$

where f_t, i_t, and $o_t$denote the forget, input, and output gates, respectively.

Gated Recurrent Unit (GRU)

GRU is an architecture of simplified recurrent neural networks which is efficient in modeling sequential information by employing update and reset gates. The GRU equations are:

$$z_t = \sigma(W_z[x_t] + b_z)r_t = \sigma(W_r[x_t] + b_r)\tilde{h}_t = tanh\left(W_h\left[\odot \quad h_{t-1}x_t\right] + b_h\right)h_t = (1 - z_t) \odot \quad h_{t-1} + z_t \odot \quad \tilde{h}_t$$

where $z_t$and $r_t$represent the update and reset gates, respectively.

Transformer (BERT/ViT)

The Transformer architecture uses a self-attention mechanism to learn about the relationships between individual words in a sequence of words and pictures. The self-attention mechanism is one that is defined as follows:

$$Attention(V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

The feed-forward network is represented as

$$FFN(x) = max(xW_1 + b_1)W_2 + b_2$$

where Q, K, and Vrepresent the query, key, and value matrices, respectively; $d_k$is the dimensionality of the key vectors; and W_1, W_2, b_1, and $b_2$denote the learnable parameters of the feed-forward network.

5. RESULTS

Table: 1 Performance of ML and DL Algorithms Across Various Domains

Category	**Algorithm**	**Healthcare**	**NLP**	**Financial Services**	**Network Security**
ML	Random Forest (RF)	0.89	0.80	0.93	0.89
	XGBoost	0.91	0.84	0.95	0.92
	LightGBM	0.90	0.83	0.94	0.91
	CatBoost	0.89	0.85	0.94	0.90
DL	CNN	0.93	0.91	0.89	0.94
	LSTM	0.90	0.89	0.91	0.90
	GRU	0.89	0.88	0.92	0.89
	Transformer (BERT/ViT)	0.94	0.93	0.94	0.96

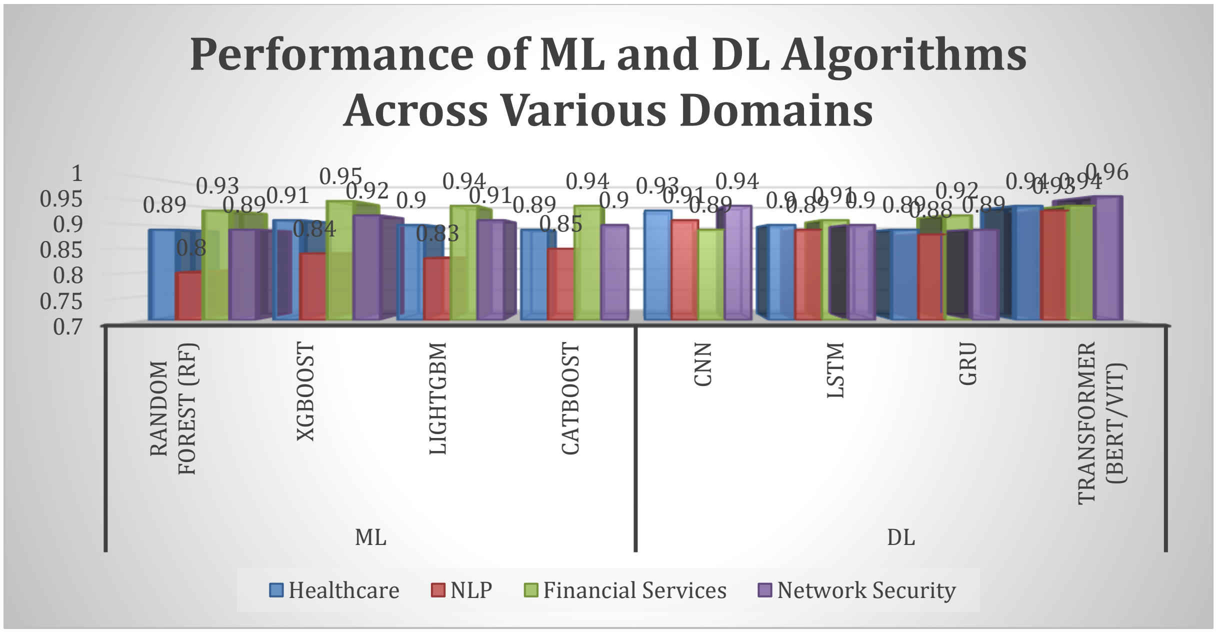

Figure 1: Performance of ML and DL Algorithms Across Various Domains

Table 1 presents the results of the tested algorithms in all four application domains: healthcare, natural language processing (NLP), financial services, and network security. Both algorithms, Machine Learning (ML) and Deep Learning (DL), exhibited good performance in these four application domains. That said, the results were different across the various datasets, based on their complexity and properties. Transformer (BERT/ViT) demonstrated the highest accuracy of 0.94 in the healthcare field, closely followed by CNN (0.93), showing that deep learning models are very precise in the medical field when it comes to detecting complex patterns.

The machine learning algorithms with the highest accuracy were XGBoost, which achieved 0.91, and LightGBM (0.90), Random Forest (0.89) and CatBoost (0.89). The Transformer (BERT/ViT) algorithm achieved the highest accuracy of 0.93 in the Natural Language Processing (NLP) domain, demonstrating the effectiveness of transformer-based models for language tasks. CNN (0.91) and LSTM (0.89) performed well as well. CatBoost scored the best accuracy (0.85), followed by XGBoost (0.84), LightGBM (0.83), and Random Forest (0.80) among all the ML algorithms. In the financial services sector, Transformer (0.94) and XGBoost (0.95) achieved great predictive results in fraud detection and financial risk assessment. LightGBM and CatBoost were also able to get accuracy 0.94, GRU (0.92) and LSTM (0.91) also performed well.

The findings suggest that both algorithms, advanced machine learning and deep learning, are suitable for structured financial data. In the network security category, the Transformer (BERT/ViT) model performed best with an accuracy of 0.96, trailed by CNN with 0.94, showing its ability to identify complex network security threats and anomalies. The best machine learning algorithms were: XGBoost (0.92), LightGBM (0.91), CatBoost (0.90), and Random Forest (0.89). Overall, the performance of deep learning algorithms was slightly better than that of machine learning algorithms in all application domains, with the greatest advantage in NLP and network security, where the feature extraction process is more complex. Even still, other sophisticated machine learning models like XGBoost, LightGBM, and CatBoost were very competitive, particularly in fields like healthcare and financial services with structured data. Based on these findings, the algorithm should be selected based on the application type, complexity of the data, the computational resources available and the accuracy of the prediction that is required.

6. CONCLUSION

This research paper conducted a comparative cross-domain analysis of Machine Learning (ML) and Deep Learning (DL) algorithms across four major application domains, namely, Healthcare, Natural Language Processing

(NLP), Financial services, and Network security. The comparative evaluation showed that both the ML and DL methods are effective tools for solving the domain-specific problem, but the DL models always outperformed the ML models in the case of complex and high dimensional data. The Transformer architecture achieved maximum overall accuracy in several domains while CNN was found to be very effective in healthcare applications. Structured datasets in healthcare and financial services were particularly well-suited for the advanced machine learning algorithms, such as XGBoost, LightGBM, CatBoost and Random Forest, which also performed competitively. The results highlight that it is important to consider the characteristics of the data, the computational needs and the application goals while selecting the right algorithm, not only the accuracy. In conclusion, the study offers useful insights into the capabilities and challenges of current ML and DL methods and can be a valuable guide for researchers and practitioners in choosing appropriate algorithms for various practical scenarios. Future studies can explore the integration of Explainable Artificial Intelligence, Transfer Learning, Federated Learning, and Hybrid ML-DL approaches to enhance cross-domain generalization, scalability, and prediction accuracy further.

REFERENCES

1. Chen, K., Zhuang, D., & Chang, J. M. (2022). Discriminative adversarial domain generalization with meta-learning based cross-domain validation. *Neurocomputing*, *467*, 418-426.
2. Kumar, A., Abhishek, K., & Shafeeq BM, A. (2025). SentXFormer: a transformer-enhanced hybrid deep learning framework for cross-domain sentiment analysis of customer reviews. *Scientific Reports*.
3. Zhu, Y., & Crowell, J. (2023). Systematic review of advancing machine learning through cross-domain analysis of unlabeled data. *Journal of Science & Technology*, *4*(1), 136-155.
4. Islam, A., Hossen, M. R., & Mahmud, T. (2026). Banglasentnet: An explainable hybrid deep learning framework for multi-aspect sentiment analysis with cross-domain transfer learning. *SN Computer Science*, *7*(5), 446.
5. Chen, Y. C., & Lee, W. C. (2024). A novel cross-domain recommendation with evolution learning. *ACM Transactions on Internet Technology*, *24*(1), 1-23.
6. Chen, K., Zhuang, D., & Chang, J. M. (2022). *Discriminative adversarial domain generalization with meta-learning based cross-domain validation*. Neurocomputing, 467, 418–426.
7. Chen, Y. C., & Lee, W. C. (2024). *A novel cross-domain recommendation with evolution learning*. ACM Transactions on Internet Technology, 24(1), 1–23.
8. Islam, A., Hossen, M. R., & Mahmud, T. (2026). *BanglaSentNet: An explainable hybrid deep learning framework for multi-aspect sentiment analysis with cross-domain transfer learning*. SN Computer Science, 7(5), 446.
9. Kumar, A., Abhishek, K., & Shafeeq, A. B. M. (2025). *SentXFormer: A transformer-enhanced hybrid deep learning framework for cross-domain sentiment analysis of customer reviews*.
10. Zhu, Y., & Crowell, J. (2023). *Systematic review of advancing machine learning through cross-domain analysis of unlabeled data*. Journal of Science & Technology, 4(1), 136–155.
11. Park, S., Hong, C. H., Lee, D., Park, K., & Shin, H. (2023). Prospective classification of Alzheimer's disease conversion from mild cognitive impairment. *Neural Networks, 164*, 335–344.
12. Wen, B., Zhou, J., Tang, P., Jia, X., Zhou, W., & Huang, J. (2023). Current progress in artificial intelligence-assisted medical image analysis for chronic kidney disease: A literature review. *Computational and Structural Biotechnology Journal*.
13. Fertier, A., Montarnal, A., Truptil, S., & Bénaben, F. (2023). Explainable prediction of loan default based on machine learning models. *Decision Support Systems*.
14. Wu, Y., Fu, Z., Liu, X., & Bing, Y. (2023). A hybrid stock market prediction model based on GNG and reinforcement learning. *Expert Systems with Applications, 228*, 120474.
15. Yuan, G. X., Zhou, Y., Liu, H., & Yan, C. (2022). The framework of CAFE credit risk assessment for financial markets in China. *Procedia Computer Science, 202*, 33–46.
16. Yue, L., Chen, W., Li, X., Zuo, W., & Yin, M. (2019). A survey of sentiment analysis in social media. *Knowledge and Information Systems, 60*(2), 617–663.
17. Savci, P., & Das, B. (2023). Comparison of pre-trained language models in terms of carbon emissions, time and accuracy in multi-label text classification using AutoML. *Heliyon, 9*(5), e15670.
18. Belal, M. M., & Sundaram, D. M. (2022). Comprehensive review on intelligent security defences in cloud: Taxonomy, security issues, ML/DL techniques, challenges and future trends. *Journal of King Saud University – Computer and Information Sciences, 34*(10), 9102–9131.
19. Catak, F. O., Kuzlu, M., Catak, E., Cali, U., & Unal, D. (2022). Security concerns on machine learning solutions for 6G networks in mmWave beam prediction. *Physical Communication, 52*, 101626.
20. Caviglione, L., Comito, C., Guarascio, M., & Manco, G. (2023). Emerging challenges and perspectives in deep learning model security: A brief survey. *Systems and Soft Computing, 5*, 200050.
21. John, M. M., Olsson, H. H., & Bosch, J. (2020). Developing ML/DL models: A design framework. *Proceedings of the IEEE/ACM International Conference on Software and System Processes*, 1–10.