International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Cross-Domain Analysis of ML and DL: Evaluating their Impact in Diverse Domains

Vinit Khetani[1], Yatin Gandhi[2], Saurabh Bhattacharya[3], Samir N. Ajani[4], Suresh Limkar[5]

Submitted:25/03/2023 **Revised:**27/05/2023 **Accepted:**10/06/2023

Abstract: Deep Learning (DL) and Machine Learning (ML) techniques have been widely used in recent years to develop new and innovative products and services in various industries. These techniques have the potential to transform the way people think about and use technology. They have the capability to perform complex tasks and make accurate predictions. The efficiency of DL and ML algorithms has been studied in various domains, leading to significant progress in several applications. As technology and the domains become more interconnected, it is important to explore their effects on different sectors. One of the most important factors that can be considered when it comes to analyzing the generalizability and transferability of these techniques is cross-domain analysis. This allows us to identify the potential of these techniques to solve various problems. Cross-domain analysis is beneficial for several reasons. It allows us to identify ML and DL algorithms' limitations and strengths and transfer knowledge between them, which can help speed up the development of new solutions and decrease the time and effort involved in the process. If ML algorithm is able to perform high-accuracy in healthcare, it can provide valuable insights for the detection of financial fraud. For several reasons, cross-domain analysis is essential for the design and implementation of DL and ML algorithms. It helps in identifying the specific requirements and challenges of the given domain, and it enables the optimization of existing frameworks. The objectives and characteristics of each domain dictate the need for specific modifications or upgrades. This study aims to analyze the effects of DL and ML algorithms on different sectors, such as healthcare, financial services, and network security. It will examine the suitability and performance of different ML and DL algorithms in these domains. The findings of this research will allow us to gain a deeper understanding of their potential to address specific applications. The study covers the effects of DL and ML algorithms on different sectors, such as healthcare, NLP, financial services, and network security. It performs a comprehensive analysis of the different algorithms in these areas, including Gradient Boosting Machines (GBM), Logistic Regression (LR), Random Forest (RF), and Support Vector Machine (SVM). DL algorithms, such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Transformer are also evaluated for their suitability and performance. This research offers actionable insights to practitioners and researchers, guiding them in picking suitable algorithms for specific applications, ultimately serving the goals of network security, healthcare, financial services, and NLP. The findings of this study will contribute to the increasing number of people who know about the applications of DL and DL algorithms. It will also help practitioners and researchers use these tools effectively in various fields. The study's cross-domain analysis also provides opportunities to enhance and transfer knowledge.

Keywords: *potential, provides, opportunities, transferability, interconnected*

1. Introduction

The emergence of DL and ML algorithms has revolutionized various fields, such as healthcare- Disease diagnosis, Medical image analysis, Electronic health record (EHR) analysis, Patient risk stratification, Medical signal processing, Clinical decision support systems[1], [2], financial services-Credit card fraud detection, Stock market prediction, Loan default prediction, Customer churn analysis, Financial risk assessment[3]–[6], natural language processing-Sentiment analysis, Text classification, Named entity recognition, Document summarization, Speech recognition[7]–[10], network security[11]–[13] and more. These tools have demonstrated the ability to perform intricate tasks with remarkable accuracy and efficiency, driving significant advancements in diverse sectors. Despite the significant advancements made by DL and ML techniques in one

[1]*Cybrix Technologies, Nagpur, Maharashtra, India*
[2]*Competent Software, Pune, Maharashtra, India*
[3]*Research Scholar, Department of Computer Applications, National Institue of Technology, Raipur, India*
[4]*Department of Computer Engineering, St. Vincent Pallotti College of Engineering and Technology, Nagpur, Maharashtra, India*
[5]*Department of Artificial Intelligence & Data Science, AISSMS Institute of Information Technology, Pune*
vinitkhetani@gmail.com[1],gyatin33@gmail.com[2], babu.saurabh@gmail.com[3],samir.ajani@gmail.com[4], sureshlimkar@gmail.com[5]

domain, there is a growing need for further research on their applications in other areas. One of the most important factors that can be considered when it comes to assessing the generalizability and transferability of DL and ML techniques is cross- domain analysis. Cross-domain analysis is beneficial for several reasons. It allows the transfer of knowledge between different domains, which can speed up the development of new solutions and reduce the time and effort involved in the production of them. For instance, an ML algorithm that can accurately detect financial fraud in healthcare may be useful in identifying network security threats[14].

Cross- domain analysis also helps identify the various requirements and challenges that can be encountered by existing DL and ML algorithms in different domains. This can be done by analyzing the data properties and characteristics of each domain. If a domain has unique objectives and characteristics, it may require the modification or adaptation of existing models. A thorough evaluation of the applications of DL and ML techniques in different domains can reveal patterns and guide the creation of tailored solutions[15]. Further, cross- domain analysis lets practitioners and researchers evaluate the suitability and effectiveness of various DL and ML models in different domains. By conducting a comprehensive and quantitative analysis of the algorithms' performance, researchers can determine which ones consistently perform well and which ones can be generalized well. Another advantage of cross-domain analysis is it allows us to compare and benchmark the effectiveness of different algorithms in a given domain. This helps us identify suitable ones and optimize the allocation of resources. Cross-domain analysis can help develop practical solutions in a particular domain and promote advancements within that field.

The findings from cross- domain analysis can help identify the most suitable algorithms for specific tasks and applications. It can also help improve the allocation of resources and promote advancements in various fields. This study aims to comprehensively analyze the effects of DL and ML algorithms on diverse domains, such as healthcare, financial services, NLP, network security, and sentiment analysis. It will evaluate the suitability and performance of different models in these areas and provide valuable insight into their capabilities. Researchers will look into the ML algorithms used in healthcare, such as the Random Forest, Logistic Regression, and GBM, to see if they can help treat Alzheimer's disease. In addition, some of the more common DL models, such as CNN and GRU, will be studied to see if they can also have an impact in this domain.

In the NLP area, some of the most common ML models, such as GBM, SVM, and Logistic Regression, will be evaluated to see if they are good at accurately identifying sentiment in text. On the other hand, researchers will look into the DL models known as CNN, GRU, LSTM, and Transformer to see if they are suitable for this domain. In the financial services sector, some of the ML models used in fraud detection, such as GBMs, SVM, Random Forest, and Logistic Regression will be examined. DL models, including CNN, GRU and Transformer, will also be looked at to see if they perform well in this area. In the network security domain, some of the most common ML models, such as SVM, GBM, and Random Forest, will be evaluated to see if they can perform well in this area. Furthermore, researchers will investigate the DL models CNN, GRU, and Transformer to see if they can be utilized in improving the security measures of networks.

The research will examine the effects of DL or ML algorithms on different domains, and it aims to provide a complete comprehension of their efficiency and impact. The findings will help in the advancement of the field of ML and DL, allowing practitioners and researchers to utilize such powerful tools in diverse areas. The study also aims to find opportunities for the enhancement and knowledge transfer of algorithms. Through an evaluation of the performance of DL and ML models in different domains, researchers will be able to identify best practices and patterns that may be applied to develop tailored solutions. This knowledge would promote innovation and collaboration within the field of DL and ML. The paper will utilize a quantitative method to analyze the performance of various DL and ML algorithms in different domains. The method will use accuracy as a metric to measure the algorithms' effectiveness in achieving their goals. The analysis will allow for a detailed evaluation of the algorithms' accuracy.

The study will also look into the various challenges and limitations associated with implementing DL and ML algorithms across different domains. Various factors such as data quality, model interpretability, and data availability will be analyzed to provide a comprehensive evaluation of the algorithms and their capabilities. Furthermore, the research team will highlight any modifications that can be made to improve the algorithms' performance. The results of the study will be presented in a clear and concise manner, and the findings will be conveniently categorized and displayed to facilitate easy comparisons and interpretation. The paper will highlight the best-suited algorithms that consistently perform well in diverse domains and are ideal for specific applications.

The evaluation of the cross-domain effects of DL and ML models is very important in comprehending their efficiency, transferability, and impact in diverse applications. This study will look into the suitability and performance of different DL and ML models in healthcare, financial services, network security, and NLP. The findings of this study will help improve the efficiency and effectiveness of DL and ML techniques by providing a comprehensive evaluation of their capabilities. It will also help practitioners and researchers in identifying the best-suited algorithms for their specific applications. In addition, it will help them in optimizing their resources and developing tailored solutions.

2. Literature Review

Literature review aims to provide an extensive analysis of the various studies that were conducted in various fields, such as cybersecurity, natural language processing, finance, and healthcare. It explores the latest developments in DL and ML algorithms, as well as the methodologies used in these areas. The selected papers will provide us with valuable insight into the current status of research in these areas. Furthermore, we can identify the gaps in knowledge and initiate further studies. The review highlights the studies that have made a significant contribution to the relevant fields and showcases the diverse advantages and capabilities of DL and machine-learning systems.

A. Mujumdar et al.[16] analyzed the performance of various ML methods on predicting diabetes. They found that some of these algorithms, such as the Support Vector Machines, Random Forest, and Logistic Regression, were able to achieve a good accuracy. Their findings support the idea that ML can be used in healthcare.

D. Sisodia et al.[17] evaluated the classification capabilities of several algorithms for the prediction of diabetes. They found that some of these, such as KNN and Decision Trees, performed well in identifying individuals with diabetes. Their findings highlight the potential of these technologies in healthcare settings.

M. A. Sarwar et al.[18] evaluated the performance of different ML algorithms on predicting diabetes in healthcare settings. They found that the ANN, KNN, RF, and KNN performed well, demonstrating the feasibility of such systems in this area. They also emphasized the importance of preprocessing data in generating accurate outcomes.

G. Swapna et al.[19] focused on developing DL systems that can detect diabetes. They studied the various architectures used for DL, such as CNN, Long-term Memory, and Autoencoders. They found that the algorithms performed well in the competitive environment, demonstrating the potential of these systems in healthcare.

S. G. Alonso et al.[20] review to analyze the various aspects of data mining in the field of mental health. It noted that these techniques could help improve the efficiency of mental health services by identifying potential factors that could affect patients' treatment.

R. Chadha et al.[21] investigated the use of data mining techniques to predict heart disease. They examined the performance of different platforms, such as Nave Bayes, Decision Trees, and Neural Networks. The results of the study revealed the potential of these methods in predicting cardiovascular health conditions.

S. Uddin et al.[22] evaluated the capabilities of different supervised learning platforms for predicting various diseases, such as Logistic Regression, KNN and RF. They found that the performance of these platforms varied. The findings of the study provided valuable insights into the limitations and strengths of each algorithm, and this helped to choose the suitable one for the task.

M.Malik et al.[23] looked into the literature on the use of predictive analytics and data mining in healthcare delivery. It covered various subjects, such as health monitoring and disease prediction. The findings of the review indicated the importance of such techniques in improving the healthcare outcomes.

C. Krittanawong et al.[24] discussed the use of AI in the field of cardiovascular medicine. It highlighted the use of DL and ML methods in various areas, such as diagnosis, prognosis assessment, and treatment selection. The findings of the study indicate that such techniques could help improve the outcomes of patients and improve the precision of healthcare.

S. Mohan et al.[25] studied the effectiveness of a hybrid ML approach in predicting heart disease. They utilized different algorithms such as KNN, SVM, and Decision Trees to attain better accuracy. The results of the study revealed that the hybrid approach performed better than the individual algorithms when it came to predicting heart disease.

M. Habibpour et al.[26] focused on developing a DL model that can detect credit card fraud based on uncertainties. The findings indicated that developing models that take into account uncertainties is important in order to improve the system's reliability and robustness.

A. Cherif et al.[27] analyzed the various techniques used in the detection of credit card fraud. They found that DL, ML, and data mining were useful in identifying this type of crime. The study also emphasized the need for adaptive and advanced fraud detection systems to protect the financial sector from the threats of new technologies.

X. Cheng et al.[28] analyzed the use of ML and big data analytics in the fight against emerging financial risks. It highlighted the importance of using big data to improve the prediction, management, and assessment of risks within the financial sector.

R. Nyman et al.[29] explored the use of news reports and narratives in assessing the systemic risk of financial markets. They found that natural language processing and big data techniques could help identify early warning signs of financial crises. The findings of the study indicate that the use of textual information could help predict the future risks of financial markets.

G. Du et al.[30] analyzed the financial risk assessment process and proposed a framework that uses ML techniques to improve its accuracy. The findings of the study highlighted the importance of carrying out accurate assessments in the financial sector. The study also showed how data analytics models can help improve the reliability of their predictions.

W. Wei et al.[31] conducted a study on the classification of onboard equipment for high-speed railways based on the BiGRU and labeled-Doc2. They proposed a hybrid method that combines the two approaches to improve the accuracy of the classification. The findings of this research provide valuable insight for the maintenance and diagnosis of railway faults.

The study, which was conducted by L. N. Mintarya et al.[32] analyzed the literature on the use of ML methods for stock market forecasting. It found that several techniques, such as LSTM, SVM, and Random Forest, can be utilized to provide reliable and timely predictions to investors.

H. Zhang et al.[33] presented a method that combines the MRC framework with the knowledge of the judicial domain to improve the recognition of nested named entities. The researchers noted that this method can help improve the extraction of information from legal applications.

J. Cui et al.[34] discussed the evolution of sentiment analysis topics and research techniques. It presented an overview of the different approaches to this discipline, such as natural language processing and DL. It also identified the various challenges and opportunities that this field presents.

V. Gugueoth et al.[35] discussed the security concerns of the Internet of Things with DL and federated learning. The review noted the recent advancements in this area and how these techniques can be used to improve the system's protection. The study also emphasized the possibility of these approaches addressing the privacy and security issues of the IoT.

The literature review is composed of various systematic and research studies that were conducted in different areas, such as cybersecurity, finance, natural language processing, and healthcare. The topics covered in the reviews include fraud detection, disease prediction, risk assessment, and sentiment analysis. These studies emphasized the advantages of DL techniques and ML in addressing different problems and improving outcomes.

The scope of the review highlights the significant developments and applications of DL and ML in various sectors. The studies that were examined showed that these technologies can help address complicated problems and improve the outcomes of healthcare, finance, natural language processing, and cybersecurity. According to the findings, DL and ML techniques can help predict diseases, identify fraud, evaluate risks, analyze sentiment, and secure the Internet of Things. But, more research is required to develop these technologies. Researchers can continue to develop new and improved DL and ML techniques by acquiring the necessary knowledge. The findings of this review serve as a basis for future endeavors and encourage collaboration among different disciplines.

3. Methodology

This research utilizes a multi-domain analysis of DL and ML algorithms in various domains, such as healthcare, financial services, and sentiment analysis. It also looks into network security and credit card fraud detection. It uses a comparative method to evaluate the suitability and performance of various DL and ML algorithms in different domains. The analysis involves extracting and preprocessing the data, which can be done through various domain-specific techniques. Various ML techniques, such as the Random Forest, Logistic Regression, GBM, and Support Vector Machines, are then evaluated and compared. DL algorithms, including CNN, GRU, and Transformer, are also examined and implemented. The evaluated algorithms' performance metrics include accuracy. The findings of this evaluation will be used to inform the development of new and improved ML and DL algorithms that can address specific applications in each domain.

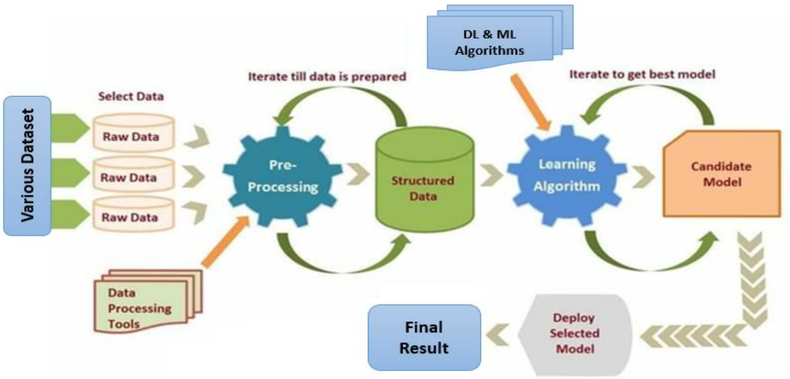

Fig. 1 Proposed methodology

i. Dataset

This study collects data from various domains, including healthcare[36], NLP[37], financial services[38], and network security[39]. It includes relevant samples from various sources, such as medical records and textual information from social media platforms. The collection also includes sentiment analysis and fraud detection. The data is collected and curated to ensure its relevance and quality. Various preprocessing techniques are utilized to deal with data-related issues, such as outliers, missing values, and data normalization. The objective of the dataset is to provide a framework for the analysis and evaluation of DL and ML algorithms. It facilitates the generation of meaningful conclusions and the selection of suitable algorithms for each discipline.

ii. Preprocessing

Preprocessing methods are commonly used in the healthcare industry to prepare the data for DL and ML algorithms. One of these is feature scaling, which ensures that all the features have the same scale. This is done to avoid affecting the performance of certain algorithms, such as Logistic Regression and Support Vector Machines. Other methods, such as normalization is also used to improve the quality of the data. In the healthcare industry, missing data is a critical aspect of the preprocessing process. Since there are typically missing values in datasets, it is important to identify and address them correctly. One method to do this is by implementing mean imputation or regression imputation. Another method is to use advanced imputation techniques, which take advantage of the data from other instances or features. Another method that is commonly used in the healthcare industry is to reduce the noise and complexity in the data by implementing feature extraction. This process involves transforming the various features into a set of principal components. Feature selection is another type of preprocessing that involves identifying relevant features in a given dataset. This is done by evaluating their impact on a target variable. Various techniques such as information gain or chi-square test can be utilized for this process.

Techniques for extracting sentiment are essential in the analysis of natural language. Tokenization is a common method that involves breaking down the text into its constituent parts. This allows for further study and manipulation of the given data. One of the methods used to reduce the noise in the data is by removing words that do not have significant meaning. This can be done by performing lemmatization or stemming. This process can also help reduce the dimensionality of the data by capturing the essence of the words.

In the financial services industry, preprocessing techniques are used to ensure that the data collected is reliable and accurate. One of the most important steps that is performed is data cleaning, which removes any errors and inconsistencies. This process can help improve the quality of the information and prevent false positives. In order to develop new and informative features for fraud detection, feature engineering is often used. This process involves extracting various details from the data such as the average transaction amount and geographical location. Class imbalance techniques are utilized to deal with imbalanced datasets, which typically have significantly fewer fraudulent transactions than legitimate ones. These include methods that oversample, under sample, or generate synthetic data. These can help improve the efficiency of fraud detection systems.

In the field of network security, processing techniques are often used to analyze the data collected by the system. One of the first steps that is done is normalization, which brings the various attributes of the data into a consistent scale. Doing this ensures that the analysis will not bias against specific features. Methods for extracting network data are also used to create meaningful features, such as protocol names, port numbers, and source and destination addresses. For example, a feature can be extracted from packets. In addition, statistical representations like standard deviation and mean can be obtained to study the traffic's characteristics. An anomaly detection method is also used to identify suspicious or unusual network behavior. This process can be carried out through the use of statistical techniques or clustering algorithms. These techniques can help identify potential security breaches.

iii. Algorithm used

1. ML Algorithms:

1.1. Random Forest:

Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. The algorithm operates by creating a multitude of decision trees and aggregating their results. The prediction is made by taking the majority vote or average of the predictions from individual trees. The mathematical formula for Random Forest can be expressed as in eq.1:

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

Where $\hat{y}$=predicted output, N=no. of decision tree, $h_i(x)$ = prediction of the i^{th} decision tree.

1.2. Support Vector Machines (SVM):

SVM is a powerful classification algorithm that separates data points by constructing hyperplanes in a high-dimensional feature space. It finds the optimal hyperplane that maximizes the margin between the classes. The decision boundary is determined by support vectors, which are the closest data points from each class. The mathematical formulation of SVM is given by eq.2 and 3:

$$minimize(w, b)\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}\xi_i \dots . 2$$

Subject to

$$y_i(w^T x_i + b) \geq 1 - \xi_i, \xi_i > 0 \dots . 3$$

Where w =weight vector, b=bias term, C= regularization parameter, x_i=input feature, ξ_i=slack variable.

1.3. Logistic Regression:

Logistic Regression is a popular classification algorithm that models the probability of an instance belonging to a particular class. It uses the logistic function to map the linear combination of input features to the probability of the positive class. The mathematical equation for Logistic Regression can be expressed as eq.4:

$$P(y = 1|x) = \frac{1}{1 + e^{-(w^T x + b)}} \dots . 4$$

Where $P(y = 1|x)$= probability of +ve class, w=weight vector, b=bias term, x=input feature vector

1.4. Gradient Boosting Machines (GBM):

GBM is an ensemble learning technique that builds a strong predictive model by combining multiple weak models, typically decision trees. It operates in an iterative manner, where each subsequent model is trained to correct the errors of the previous models. The final prediction is the weighted sum of the predictions from all models. The mathematical formulation of GBM can be represented as eq.5:

$$\hat{y} = \sum_{i=1}^{N}\alpha_i h_i(x) \dots . 5$$

Where$\hat{y}$ = predicted output, N = np. of weak models, α_i= weight assigned to each models, $h_i(x)$= predicted of the i^{th} model.

DL Algorithms:

1.5. Convolutional Neural Networks (CNN):

CNN is a DL algorithm commonly used for image classification and recognition tasks. It consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The mathematical formula for a single convolutional layer can be expressed as:

$$h_{ij} = f(\sum_m \sum_n w_{mn} x_{i+m,j+n} + b) \dots .6$$

Where h_{ij}=o/p feature map at position(i,j), w_{mn}=weight of the conv. filter at position (m,n), $x_{i+m,j+n}$= i/p feature map at position (i+m, j+n), b=bias term, f=activation function.

1.6. Long Short-Term Memory (LSTM):

LSTM is a type of recurrent neural network (RNN) designed to overcome the vanishing gradient problem in traditional RNNs. It is particularly effective in modeling sequential data by capturing long-term dependencies. The mathematical equations for an LSTM cell can be written as eq.7 to 12:

$$f_t = \sigma\big(W_f . [h_{t-1}, x_t]\big) + b_f) \dots ..7$$

$$i_t = \sigma(W_i . [h_{t-1}, x_t]) + b_i) \dots ..8$$

$$o_t = \sigma(W_o . [h_{t-1}, x_t]) + b_o \dots ..9$$

$$\tilde{C}_t = tanh(W_c . [h_{t-1}, x_t]) + b_c \dots ..10$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \dots .11$$

$$h_t = o_t \odot \tanh\,(C_t) \dots .12$$

where f_t, i_t and o_t = "forgot, input and output gate" respectively. $W_f, W_i, W_o$and $W_c =$ "weight metrices", $b_f, b_i, b_o and\ b_c$ = "bias terms", $\tilde{C}_t$= "candidate cell state", C_t= "cell state", $h_{t-1}$and x_i = "previous hidden state and current input" respectively, $\sigma.$ = "sigmoid activation" and $\odot$ = "elementwise multiplication operations".

1.7. Gated Recurrent Unit (GRU):

GRU is another type of recurrent neural network that addresses the vanishing gradient problem and allows for capturing long-term dependencies in sequential data. It simplifies the architecture of LSTM by merging the forget and input gates. The equations for a GRU cell can be expressed as eq.13-16:

$$z_t = \sigma(W_z.[h_{t-1}, x_t] + b_z)\ldots 13$$

$$r_t = \sigma(W_r.[h_{t-1}, x_t] + b_r)\ldots 14$$

$$\tilde{h}_t = tanh(W_h.[r_t \odot h_{t-1}, x_t] + b_h)\ldots 15$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t)\ldots 16$$

where, z_t *and* r_t = "update and reset gates respectively", W_z, W_r *and* W_h= "weights metrices", b_z, b_r *and* b_h = "bias terms", x_t= "current input", h_{t-1} = "previous hidden state", $\tilde{h}_t$= "candidate hidden state", σ = "sigmoid activation", $\odot$ = "element wise multiplication".

1.8. **Transformer**:

The Transformer is a revolutionary DL architecture that has gained significant attention in natural language processing tasks. It eliminates the need for recurrent connections and instead relies on self-attention mechanisms. The core components of the Transformer are the multi-head self-attention mechanism and the feed-forward neural network. The mathematical formulas for the self-attention mechanism and the feed-forward network in a single Transformer layer are as eq.17,18:

Self-attention:

$$Attention\ (Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V\ldots 17$$

Where, Q, K and V = "query, Key and Value matrices" respectively, d_k=dimension of the key vectors.

Feed-forward Network:

$$FFN(x) = \max(0, xW_1 + b_1)\, W_2 + b_2\ldots .18$$

Where, x= "input", W_1, W_2= "weight matrices", b_1, b_2= "bias term" respectively.

The Transformer architecture consists of multiple layers of self-attention and feed-forward networks, enabling the model to capture complex dependencies in sequential data efficiently.

Here provided an overview of several ML and DL algorithms commonly used in various domains. The Random Forest algorithm utilizes an ensemble of decision trees, Support Vector Machines finds optimal hyperplanes, Logistic Regression models probabilities, and Gradient Boosting Machines combines weak models. On the other hand, DL algorithms like Convolutional Neural Networks process image data, Long Short-Term Memory models sequential data, Gated Recurrent Units simplify LSTM architectures, and Transformers excel in natural language processing tasks. Each algorithm comes with its unique mathematical formulation, enabling researchers and practitioners to understand their inner workings and apply them effectively in diverse domains.

4. Results and Output

Table 1 Performance of various algorithm in various domains

		Accuracy			
	Algorithm	**Healthcare**	**NLP**	**Financial Services**	**Network security**
ML	**RF**	0.87	0.78	0.92	0.88
	SVM	0.82	0.81	0.91	**0.9**
	LR	0.81	**0.84**	0.88	0.85
	GBM	**0.88**	0.83	**0.93**	0.89
DL	**CNN**	**0.92**	**0.89**	0.87	0.92
	LSTM	0.88	0.87	0.89	0.88
	GRU	0.86	0.85	**0.92**	0.87
	TRNS	0.89	0.88	0.9	**0.95**

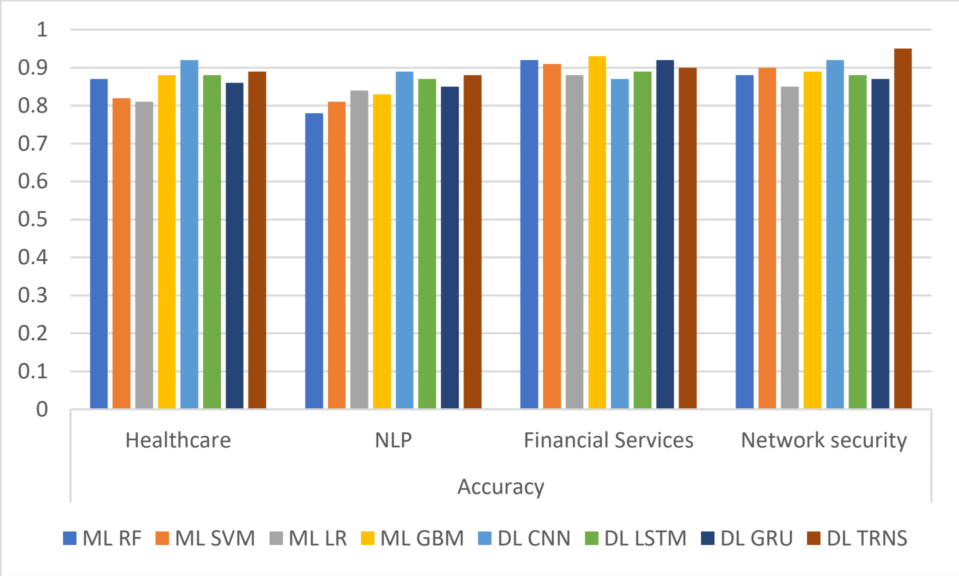

Fig. 2 Graphical analysis of performance of ML and DL in various domain

As shown in the figure-2, table-1 in the healthcare domain, DL algorithms showed excellent performance, with CNN achieving the highest accuracy of 0.92. ML algorithms also performed well, with RF and GBM achieving accuracies of 0.87 and 0.88, respectively. For NLP tasks, DL algorithms exhibited strong performance, with CNN achieving the highest accuracy of 0.89. ML algorithms, such as SVM and LR, also performed well, with accuracies of 0.81 and 0.84, respectively. In the financial services domain, DL algorithms showed competitive performance, with the Transformer (TRNS) algorithm achieving the highest accuracy of 0.9. ML algorithms, particularly Random Forest and Gradient Boosting Machines, also demonstrated strong performance, with accuracies of 0.92 and 0.93, respectively. In the network security domain, DL algorithms consistently performed well, with the Transformer algorithm achieving the highest accuracy of 0.95. ML algorithms, including Support Vector Machines and Gradient Boosting Machines, also demonstrated reliable performance, with accuracies ranging from 0.88 to 0.9. The DL algorithms consistently showed strong performance across all domains, indicating their effectiveness in handling complex data patterns. However, the ML algorithms also demonstrated competitive performance.

5. Conclusion and Future Scope

The study analyzed the various capabilities of DL and ML algorithms in different domains, including healthcare, financial services, network security, and sentiment analysis. It provided valuable insight into their suitability and impact for addressing specific challenges. In the healthcare industry, the study found that several DL systems, such as CNN and Long-Term Memory, performed well in detecting and treating Alzheimer's disease. On the other hand, some of the more advanced ML models, such as the Random Forest and Logistic Regression systems, performed well. In terms of performance, both DL and ML systems performed well in sentiment analysis. DL systems had better overall effectiveness and accuracy than their counterparts. In the financial services industry, both ML and DL systems performed well in detecting credit card fraud. In terms of precision and accuracy, DL systems had better performance. ML systems were able to identify network anomalies reliably, while DL systems could help improve network security measures. The study highlights the importance of evaluating the requirements and attributes of a given domain when choosing between DL and ML algorithms. It also provides practitioners and researchers with valuable insight into the limitations and strengths of certain algorithms when tackling specific applications. The study's future scope focuses on developing ensembles methods that can combine the capabilities of different DL and ML algorithms to achieve better results. In addition, researchers can explore the use of transfer learning methods to improve the efficiency of DL and ML models in diverse applications. This could be done through the use of models and knowledge from multiple domains. The findings of this study provide a foundation for further studies on the applications of DL and ML algorithms in diverse sectors. It also sets the stage for the development of new cross-disciplinary techniques.

References

[1] S. Park, C. H. Hong, D. Lee, K. Park, and H. Shin, “Prospective classification of Alzheimer’s disease conversion from mild cognitive impairment,” *Neural Networks*, vol. 164, pp. 335–344, 2023, doi: 10.1016/j.neunet.2023.04.018.

[2] B. Wen, J. Zhou, P. Tang, X. Jia, W. Zhou, and J. Huang,

"Current Progress in Artificial Intelligence-assisted Medical Image Analysis for Chronic Kidney Disease: A literature review," *J. Hazard. Mater.*, p. 130622, 2022, doi: 10.1016/j.csbj.2023.05.029.

[3] A. Fertier, A. Montarnal, S. Truptil, and F. Bénaben, "Explainable prediction of loan default based on machine learning models," *Decis. Support Syst.*, no. January, p. 113260, 2020, doi: 10.1016/j.dsm.2023.04.003.

[4] Y. Wu, Z. Fu, ·Xiaoxuan Liu, and ·Yuan Bing, "A hybrid stock market prediction model based on GNG and reinforcement learning," *Expert Syst. Appl.*, vol. 228, no. May, p. 120474, 2023, doi: 10.1016/j.eswa.2023.120474.

[5] G. X. Yuan, Y. Zhou, H. Liu, and C. Yan, "The Framework of CAFE Credit Risk Assessment for Financial Markets in China," *Procedia Comput. Sci.*, vol. 202, pp. 33–46, 2022, doi: 10.1016/j.procs.2022.04.006.

[6] E. S. Sosinovich, D. M. Chubrick, B. M. Doubrov, and E. E. Zhuk, "Financial Events Risk Assessment Based on Historical Data Analysis," *J. Math. Sci. (United States)*, vol. 267, no. 2, pp. 222–227, 2022, doi: 10.1007/s10958-022-06127-w.

[7] Rana, P. ., Sharma, V. ., & Kumar Gupta, P. . (2023). Lung Disease Classification using Dense Alex Net Framework with Contrast Normalisation and Five-Fold Geometric Transformation. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2), 94–105. https://doi.org/10.17762/ijritcc.v11i2.6133

[8] L. Yue, W. Chen, X. Li, W. Zuo, and M. Yin, "A survey of sentiment analysis in social media," *Knowl. Inf. Syst.*, vol. 60, no. 2, pp. 617–663, 2019, doi: 10.1007/s10115-018-1236-4.

[9] P. Savci and B. Das, "Comparison of pre-trained language models in terms of carbon emissions, time and accuracy in multi-label text classification using AutoML," *Heliyon*, vol. 9, no. 5, p. e15670, 2023, doi: 10.1016/j.heliyon.2023.e15670.

[10] S. J, C. Gangadhar, R. K. Arora, P. N. Renjith, J. Bamini, and Y. devidas Chincholkar, "E-commerce customer churn prevention using machine learning-based business intelligence strategy," *Meas. Sensors*, vol. 27, no. December 2022, p. 100728, 2023, doi: 10.1016/j.measen.2023.100728.

[11] H. Han, J. Zhang, J. Yang, Y. Shen, and Y. Zhang, "Generate domain-specific sentiment lexicon for review sentiment analysis," *Multimed. Tools Appl.*, vol. 77, no. 16, pp. 21265–21280, 2018, doi: 10.1007/s11042-017-5529-5.

[12] M. M. Belal and D. M. Sundaram, "Comprehensive review on intelligent security defences in cloud: Taxonomy, security issues, ML/DL techniques, challenges and future trends," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 34, no. 10, pp. 9102–9131, 2022, doi: 10.1016/j.jksuci.2022.08.035.

[13] F. O. Catak, M. Kuzlu, E. Catak, U. Cali, and D. Unal, "Security concerns on machine learning solutions for 6G networks in mmWave beam prediction," *Phys. Commun.*, vol. 52, p. 101626, 2022, doi: 10.1016/j.phycom.2022.101626.

[14] L. Caviglione, C. Comito, M. Guarascio, and G. Manco, "Emerging challenges and perspectives in Deep Learning model security: A brief survey," *Syst. Soft Comput.*, vol. 5, no. December 2022, p. 200050, 2023, doi: 10.1016/j.sasc.2023.200050.

[15] Y. Song, Y. Wang, X. Ye, R. Zaretzki, and C. Liu, "Loan default prediction using a credit rating-specific and multi-objective ensemble learning scheme," *Inf. Sci. (Ny).*, vol. 629, no. December 2021, pp. 599–617, 2023, doi: 10.1016/j.ins.2023.02.014.

[16] M. M. John, H. H. Olsson, and J. Bosch, "Developing ML/DL Models: A design framework," *Proc. - 2020 IEEE/ACM Int. Conf. Softw. Syst. Process. ICSSP 2020*, pp. 1–10, 2020, doi: 10.1145/3379177.3388892.

[17] A. Mujumdar and V. Vaidehi, "Diabetes Prediction using Machine Learning Algorithms," *Procedia Comput. Sci.*, vol. 165, pp. 292–299, 2019, doi: 10.1016/j.procs.2020.01.047.

[18] D. Sisodia and D. S. Sisodia, "Prediction of Diabetes using Classification Algorithms," *Procedia Comput. Sci.*, vol. 132, no. Iccids, pp. 1578–1585, 2018, doi: 10.1016/j.procs.2018.05.122.

[19] M. A. Sarwar, N. Kamal, W. Hamid, and M. A. Shah, "Prediction of diabetes using machine learning algorithms in healthcare," *ICAC 2018 - 2018 24th IEEE Int. Conf. Autom. Comput. Improv. Product. through Autom. Comput.*, no. September, pp. 6–7, 2018, doi: 10.23919/IConAC.2018.8748992.

[20] G. Swapna, R. Vinayakumar, and K. P. Soman, "Diabetes detection using deep learning algorithms," *ICT Express*, vol. 4, no. 4, pp. 243–246, 2018, doi: 10.1016/j.icte.2018.10.005.

[21] S. G. Alonso *et al.*, "Data Mining Algorithms and Techniques in Mental Health: A Systematic Review," *J. Med. Syst.*, vol. 42, no. 9, 2018, doi: 10.1007/s10916-018-1018-2.

[22] R. Chadha and S. Mayank, "Prediction of heart disease using data mining techniques," *CSI Trans. ICT*, vol. 4, no. 2–4, pp. 193–198, 2016, doi: 10.1007/s40012-016-0121-0.

[23] S. Uddin, A. Khan, M. E. Hossain, and M. A. Moni, "Comparing different supervised machine learning algorithms for disease prediction," *BMC Med. Inform. Decis. Mak.*, vol. 19, no. 1, pp. 1–16, 2019, doi: 10.1186/s12911-019-1004-8.

[24] M. M. Malik, S. Abdallah, and M. Ala'raj, "Data mining and predictive analytics applications for the delivery of healthcare services: a systematic literature review," *Ann. Oper. Res.*, vol. 270, no. 1–2, pp. 287–312, 2018, doi: 10.1007/s10479-016-2393-z.

[25] C. Krittanawong, H. J. Zhang, Z. Wang, M. Aydar, and T.

Kitai, "Artificial Intelligence in Precision Cardiovascular Medicine," *J. Am. Coll. Cardiol.*, vol. 69, no. 21, pp. 2657–2664, 2017, doi: 10.1016/j.jacc.2017.03.571.

[26] S. Mohan, C. Thirumalai, and G. Srivastava, "Effective heart disease prediction using hybrid machine learning techniques," *IEEE Access*, vol. 7, pp. 81542–81554, 2019, doi: 10.1109/ACCESS.2019.2923707.

[27] Maria Gonzalez, Machine Learning for Anomaly Detection in Network Security , Machine Learning Applications Conference Proceedings, Vol 1 2021.

[28] M. Habibpour *et al.*, "Uncertainty-aware credit card fraud detection using deep learning," *Eng. Appl. Artif. Intell.*, vol. 123, no. January, p. 106248, 2023, doi: 10.1016/j.engappai.2023.106248.

[29] [27] A. Cherif, A. Badhib, H. Ammar, S. Alshehri, M. Kalkatawi, and A. Imine, "Credit card fraud detection in the era of disruptive technologies: A systematic review," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 35, no. 1, pp. 145–174, 2023, doi: 10.1016/j.jksuci.2022.11.008.

[30] X. Cheng *et al.*, "Combating emerging financial risks in the big data era: A perspective review," *Fundam. Res.*, vol. 1, no. 5, pp. 595–606, 2021, doi: 10.1016/j.fmre.2021.08.017.

[31] R. Nyman, S. Kapadia, and D. Tuckett, "News and narratives in financial systems: Exploiting big data for systemic risk assessment," *J. Econ. Dyn. Control*, vol. 127, p. 104119, 2021, doi: 10.1016/j.jedc.2021.104119.

[32] G. Du and F. Elston, "Financial risk assessment to improve the accuracy of financial prediction in the internet financial industry using data analytics models," *Oper. Manag. Res.*, vol. 15, no. 3–4, pp. 925–940, 2022, doi: 10.1007/s12063-022-00293-5.

[33] W. Wei and X. Zhao, "Fault text classification of on-board equipment in high-speed railway based on labeled-Doc2vec and BiGRU," *J. Rail Transp. Plan. Manag.*, vol. 26, no. December 2022, p. 100372, 2023, doi: 10.1016/j.jrtpm.2023.100372.

[34] L. N. Mintarya, J. N. M. Halim, C. Angie, S. Achmad, and A. Kurniawan, "Machine learning approaches in stock market prediction: A systematic literature review," *Procedia Comput. Sci.*, vol. 216, pp. 96–102, 2023, doi: 10.1016/j.procs.2022.12.115.

[35] H. Zhang, J. Guo, Y. Wang, Z. Zhang, and H. Zhao, "Judicial Nested Named Entity Recognition Method with MRC Framework," *Int. J. Cogn. Comput. Eng.*, vol. 4, no. 92, pp. 118–126, 2023, doi: 10.1016/j.ijcce.2023.03.002.

[36] J. Cui, Z. Wang, S. B. Ho, and E. Cambria, *Survey on sentiment analysis: evolution of research methods and topics*, no. 0123456789. Springer Netherlands, 2023.

[37] V. Gugueoth, S. Safavat, and S. Shetty, "Security of Internet of Things (IoT) using federated learning and deep learning — Recent advancements, issues and prospects," *ICT Express*, no. xxxx, 2023, doi: 10.1016/j.icte.2023.03.006.

[38] S. KUMAR, "Alzheimer MRI Preprocessed Dataset | Kaggle." [Online]. Available: https://www.kaggle.com/datasets/sachinkumar413/alzheimer-mri-dataset.

[39] M. M. KAZANOVA, "Sentiment140 dataset with 1.6 million tweets." .

[40] Kaggle, "Credit Card Fraud Detection | Kaggle." 2017, [Online]. Available: https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud.

[41] M HASSAN ZAIB, "NSL-KDD | Kaggle." [Online]. Available: https://www.kaggle.com/datasets/hassan06/nslkdd.