OPEN ACCESS
International Journal of Innovations in Science & Technology

Integrating Machine Learning and Neural Approaches for Predictive and Analytical Tasks: A Comprehensive Review

Hadia Khalid, Bushra Khan, Mahnoor Tunio, Sobia Soomro
Department of Computer Science, Quaid-e-Awam University of Engineering Science & Technology, Nawabshah, Sindh
***Correspondence**: mughalhayafatima@gmail.com

Citation | Khalid. H, Khan. B, Tunio. M, Soomro. S, "Integrating Machine Learning and Neural Approaches for Predictive and Analytical Tasks: A Comprehensive Review", IJIST, Vol. 7 Issue. 10 pp 311-328, December 2025
Received| November 28, 2025 **Revised|** December 20, 2025 **Accepted|** December 23, 2025 **Published|** December 27, 2025.

This study aims to review and analyze recent research on Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and Artificial Neural Networks (ANN) for predictive and analytical tasks across domains such as education, healthcare, software engineering, and materials science. The paper examines the methodologies, tools, and performance metrics of these techniques by analyzing seven recent studies. A comparative analysis is conducted using key evaluation parameters, including accuracy, precision, recall, F1-score, and efficiency. The findings indicate that Deep Learning and ANN models demonstrate higher predictive accuracy in complex analytical problems, particularly in image-based and engineering applications. NLP methods show strong performance in text processing and language-related tasks, while ML approaches are effective for structured data analysis and decision-making applications. The review highlights the strengths and limitations of each approach and identifies potential directions for future research in integrating these techniques for improved predictive performance.

Keywords: Machine Learning, Deep Learning, Natural Language Processing, Artificial Neural Networks, Predictive Analytics, Comparative Analysis

Introduction:

Machine Learning (ML), Deep Learning (DL), Artificial Neural Networks (ANN), and Natural Language Processing (NLP) have become among the most popular technologies in order to solve real-life problems. Such methods have now been used in numerous other areas, including medicine, education, software engineering, cultural studies, and materials science. Due to their fast development, it is now important to know how such methods operate, how they are used, and what their strengths and weaknesses are.

ML finds application in cultural heritage not only for prediction but also for developing ethical frameworks. One of the studies was devoted to the analysis of available ML projects and developed a checklist that helps to make the use of ML responsible and transparent when working with museum and heritage data [1]. On the contrary, the application of ML in education is more realistic. The recent platform enabled schoolchildren to create small ML-based applications, and findings demonstrated that children could learn how to interpret the process of ML and construct classifier applications in a productive way [2]. Deep Learning techniques have been especially useful in visual analysis. The CNN-based study in healthcare was able to classify scalp diseases with high accuracy on image preprocessing and automated model tuning [3]. Large Language Models have also been used with DL to identify software vulnerabilities. Such a hybrid approach enhanced the precision and decreased false positives in computer security work [4]. NLP methods are also on the increase. The Moroccan dialect of the French variety called Darija has been trained with a large-scale BERT model with excellent validation accuracy, enhancing the NLP resources of low-resource languages [5]. In another study, Transformer models were fine-tuned to differentiate between human-written and AI-written academic texts, and it was demonstrated that the use of fine-tuning significantly enhances the detection of authorship [6]. In addition to ML and NLP, ANN models are also used in materials science and engineering, besides ML and NLP. An experiment that integrated Response Surface Methodology (RSM) and ANN had very high prediction accuracy of joint properties in the welding joint, and optimal welding parameters were also established [7].

In general, the studied articles demonstrate that ML, DL, ANN, and NLP methods are not restricted to a particular type of work. The performance of DL and ANN models is good in predictive and analytical problems, particularly in applications in image and materials science. NLP models can be better used in text processing and tasks that involve language. Other studies emphasize the educational or ethical applications of ML and not numerical accuracy. The various applications are synthesized in this review to point out how various techniques are applied, the type of results achieved by them, and what gaps in research remain.

Literature Review:

This section reviews previous studies related to Machine Learning, Deep Learning, Natural Language Processing, and Artificial Neural Networks. The focus is on the methodologies used in these studies, while the performance results are analyzed separately in the results section.

It is challenging to establish broad rules for machine learning in biology due to the diversity of biological data. Therefore, our goal is to provide biologists with an overview of the various approaches that are accessible, as well as some suggestions on how to use their data for efficient machine learning [8].

After being trained on some initial training data, a machine learning model with incremental or decremental features is used to handle new data that is received as a stream. The model should be able to produce accurate predictions for incoming testing data and be able to be adjusted appropriately for receiving additional training data. Retraining should ideally not be necessary during the procedure, based on storing all received data [9].

The ANN-ISM paradigm links information security management with an Artificial Neural Network to spot and regulate cyber threats successfully. The ANN system uses recent and past data to recognize security dangers, while the ISM framework maintains policies for running security tasks in a planned method [10].

Our study of actual biological brain networks undoubtedly gives birth to the high-level notion that numerous such units may be coupled, given the right connectivity and learning algorithm, to produce far more fascinating and complicated behavior than any one neuron alone could represent. However, the majority of deep learning research nowadays is inspired by a far broader source [11].

Additionally, DL can be used in experiments to enhance the quality of the actual data. This can boost the quantity of information captured in each image or save the time needed to collect data. Additionally, DL techniques such as super-resolution can be used in situ to independently modify experimental settings [12].

Deep learning (DL) is regarded as a development of machine learning (ML) that uses algorithms to learn from data in order to perform certain tasks without explicit programming. Deep learning enables machines to see the world as a hierarchy of concepts and learn from their errors [13].

Machine learning and computational linguistics are widely utilized in natural language processing, an essential branch of computer science. The primary goal of this field is to make computer-human interaction simple and effective. A machine learns human language's grammar and meaning, processes it, and outputs the results to the user. NLP is the study of using natural, human-understandable language to enable computer systems to carry out useful activities [14].

NLP has the potential to enhance educational technology in a number of ways, including its ability to analyze language and data and produce relevant results. Emphasizing speaking, writing, and reading can enhance language-related education [15].

ChatGPT's sophisticated natural language processing capabilities enable it to precisely comprehend and react to complicated queries, increasing the efficacy and efficiency of virtual assistants, customer service, and other interactive applications [16]

Since the network is always re-initialized before optimization, the majority of studies that use ANNs to reduce the dimensionality of design representation do not rely on conventional learning techniques [17].

The multivalued neural network is more effective to utilize if the data pretreatment is extremely complex and demanding, particularly in a multidimensional input space, because it addresses the non-uniqueness issue without requiring data preprocessing [18].

Digital encoding is utilized for external routing and processing, whereas crossbar calculations are carried out in the analog domain. The conversion between the analog and digital domains is the primary issue in the design of memristive ANNs, even though each block in the peripheral circuit requires a significant amount of work on its own [19].

Contribution:

This review is unique in that it is unified and comparative, providing an approach to the analysis of the concepts of Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and Artificial Neural Network (ANN) in the same framework. This is in contrast to the other review studies, whose methodologies are limited to one technique or field of application and compare them based on the results of similar performance metrics (e.g., accuracy, precision, recall, F1-score, and efficiency). Moreover, the paper contains a graphical comparison between the works of choice that allows one to better understand the strengths, limitations, and performance patterns of various learning paradigms. Such a centralized approach helps the researchers in choosing relevant methods in predictive and analytical activities and indicates gaps in available research that can be used in future studies.

Methodology:

This review paper adopts a structured, multi-stage methodology to systematically examine seven research studies across four major computational technologies: Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and Artificial Neural Networks (ANN). The methodology focuses on extracting, categorizing, and synthesizing the experimental designs, tools, datasets, and modeling techniques used in each study. This enables a comparative understanding of how different computational approaches are applied across diverse domains such as education, medical imaging, welding optimization, software security, and text analysis.

The materials used in this review include seven recent research articles published between 2020 and 2025 focusing on Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and Artificial Neural Networks (ANN). These studies were analyzed based on their methodologies, datasets, and performance metrics. The comparison was conducted using evaluation parameters such as accuracy, precision, recall, F1-score, and efficiency. Comparative charts were generated to visually analyze the performance of the reviewed approaches.

Machine Learning (ML):

Machine Learning is a key area of artificial intelligence that allows computational systems to develop patterns from data without being specially written to perform specific tasks. The models described in ML process existing data, determine statistical associations, and apply the patterns to make inferences or decisions on unknown data. Three key learning paradigms are the foundation of the field, namely, supervised, unsupervised, and reinforcement learning. In supervised learning, the models are trained with labeled data, but in unsupervised learning, it aims at identifying the hidden patterns in unlabeled data. In reinforcement learning, an agent can engage with an environment and optimise its performance depending on indicators of rewards. Although it has some advantages, especially when it is used with structured data, ML is very slow and expensive to compute features by hand and therefore limits the ability to capture complex high-dimensional patterns, which is especially a problem in large-scale contexts. The need to overcome these limitations led to the creation of more advanced data-driven approaches, which eventually led to the design of Deep Learning.

Supervised Learning:

The most common type of Machine Learning is Supervised Learning, where the models are trained with labeled data, which includes input-output pairs. It aims to learn a mapping between features and the appropriate target values. Some of the algorithms in this category are Logistic Regression, Linear Regression, Decision Trees, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and types of Neural Networks. Supervised learning is generally used in tasks such as classification and regression. In the literature reviewed, a direct example of this type is Logistic Regression, because this type of model is based on labeled data and pre-determined classes to train and evaluate the model.

Unsupervised Learning:

Unsupervised Learning uses unlabeled data and aims at finding latent structures, patterns, or relationships in the data. The model learns autonomously since it does not have any preset outputs and finds similarities and natural groupings. Some of the commonly used methods are the clustering methods (K-Means and Hierarchical Clustering) and the dimensionality reduction methods (Principal Component Analysis (PCA)). Though unsupervised learning methods were not used in any of the reviewed papers, this type is one of the core ones in the wider scope of the Machine Learning framework and is needed in tasks of pattern discovery or compression of data.

Reinforcement Learning: Reinforcement Learning is a name for a particular subdivision of Machine Learning where an agent interacts with an environment and learns how to behave best with the help of feedback in the form of rewards and penalties. Rather than studying in the absence of dynamism, the agent makes better decisions as time progresses by trying out actions and analyzing their consequences. Reinforcement Learning is used extensively in robotics, games, and autonomous systems. Although this type has not been used in the papers reviewed, it is a significant expansion of the conventional methods of machine learning and a full extension of the general hierarchy of machine learning strategies.

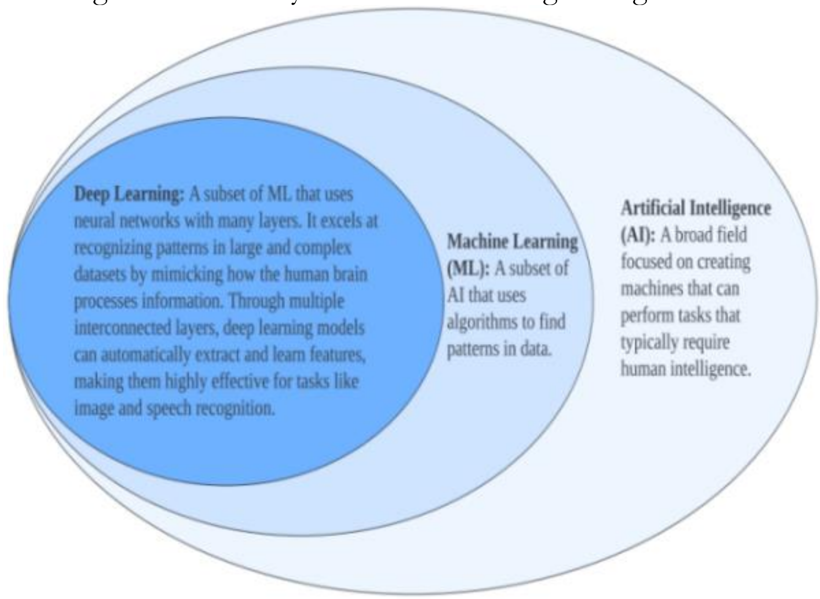

Figure 1. Interrelationship between Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL), illustrating their hierarchical structure where ML is a subset of AI and DL is a specialized subset of ML. [20]

Figure 1 shows the hierarchical relationship between Artificial Intelligence, Machine Learning, and Deep Learning.

Deep Learning (DL):

Deep Learning is a sophisticated branch of Machine Learning that employs multi-layered artificial neural networks to model complex patterns in large and unstructured data. Compared to conventional ML methods, DL models can automatically learn relevant features from raw data, enabling them to work with images, audio, video, and natural language with impressive accuracy. Convolutional Neural Networks (CNNs) based on Deep Learning are useful in image processing, whereas Recurrent Neural Networks (RNNs), including LSTM and GRU, are useful in processing sequential, speech, or time-series data. During the past few years, transformer-based models have transformed DL with their self-attention mechanisms and enabling highly efficient processing of long sequences and capturing deep contextual relationships. Even though Deep Learning has provided state-of-the-art performance in various fields, the challenges are significant, including very large datasets and massive computational power are required, and training takes more time. However, it is still one of the most powerful technologies of contemporary AI.

Convolutional Neural Networks (CNNs):

One of the most common types of deep learning architectures is Convolutional Neural Networks (CNNs), which are particularly popular when working with images. CNNs learn spatial features automatically by using convolutional filters, pooling, and hierarchical feature extraction. They are best suited to classification, detection, and segmentation. CNNs were used in the reviewed articles to categorize scalp diseases on an AutoKeras-optimized architecture, which demonstrates their effectiveness in medical imaging and pattern recognition.

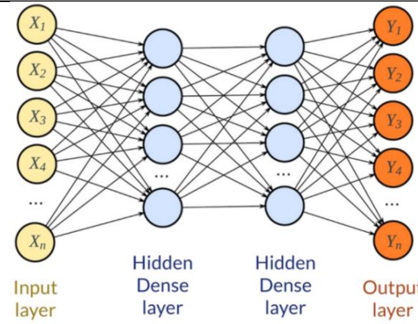

Figure 2: Architecture of an Artificial Neural Network (ANN) illustrating the flow of data from the input layer through multiple hidden layers to the output layer, demonstrating how neural networks learn complex patterns for predictive and analytical tasks. [20]

Figure 2 illustrates the architecture of an Artificial Neural Network and the flow of data through its layers.

Recurrent Neural Networks (RNNs):

Recurrent Neural Networks are designed for sequential and time-dependent data. Compared to CNNs, RNNs process one step at a time but retain previous information using internal memory. Other variants, like LSTMs and GRUs, are designed to address problems such as vanishing gradients. Although RNNs have not been explicitly applied in the papers analyzed in this review of DL works, they are a fundamental category of DL commonly applied in speech recognition, language modeling, and time-series analysis.

Transformer Models:

Transformers are a more complex DL model developed based on self-attention mechanisms, which enable models to capture long-range dependencies better than RNNs. They have also become dominant in both NLP and advanced DL tasks. Hybrid DL systems using Transformer-based LLMs to detect vulnerabilities, as described in the reviewed studies, demonstrate that Transformers extend deep learning to non-vision tasks, including reasoning and understanding code and text.

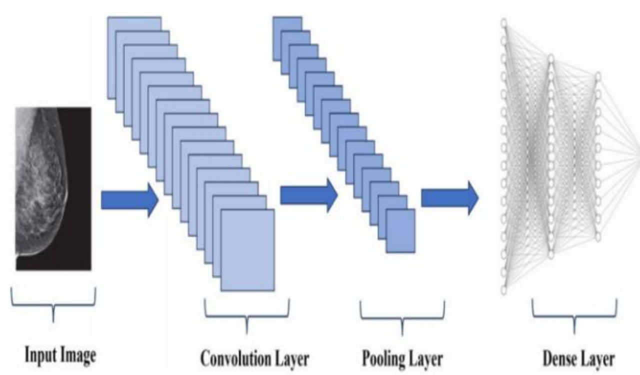

Figure 3. Workflow of a Convolutional Neural Network (CNN) illustrating input image processing, convolution operations, pooling layers, and fully connected (dense) layers for feature extraction and classification in deep learning models. [20]

Figure 3 demonstrates the workflow of a Convolutional Neural Network (CNN), including convolution, pooling, and classification stages.

Natural Language Processing (NLP):

Natural Language Processing refers to the field of artificial intelligence that aims to help machines comprehend, analyze, interpret, and produce human language. NLP is designed to reduce the language barrier between humans and computers using linguistic, statistical, and deep learning methods. Conventional NLP was based on rule-based technologies and traditional statistical techniques like Bag-of-Words and TF-IDF, which could not effectively capture context, semantics, and long-range linguistic relationships. The introduction of Deep Learning and transformer models, such as BERT and GPT, has enabled NLP systems to understand context much better. These models use self-attention mechanisms to model relationships between words in long sequences and are therefore very useful in a wide range of tasks, including text classification, sentiment analysis, question answering, translation, summarization, and conversational AI. However, despite challenges such as language ambiguity and cultural variations, NLP has become one of the core elements of modern AI usage because of its ability to process large volumes of unstructured text information with a high level of accuracy.

Statistical NLP:

The classical language processing algorithms (using probability, statistics, and classical machine learning) are known as statistical NLP. Examples of such methods include logistic regression, n-grams, and rule-based filters. In one of the papers you have read, logistic regression was employed alongside rule-based filtering in handling Moroccan Arabic text, demonstrating that statistical NLP is still useful with structured tasks.

Neural NLP:

Neural NLP aims to learn language representations with the help of deep learning architectures, including CNNs, RNNs, and Transformers, particularly on large datasets. Fine-tuned Transformer models, such as BERT, have been used to identify AI-generated texts and categorize dialects in your reviewed papers. Neural NLP represents the state of the art in language understanding and achieves state-of-the-art performance on most tasks.

Hybrid NLP:

Hybrid NLP combines statistical techniques, machine learning, and deep learning with human-written rules to enhance performance and interpretability. This strategy is particularly useful for low-resource languages, like Moroccan Darija, are used, where scraping, rules, and ML methods together are more effective in classifying them. A number of the reviewed articles used hybrid NLP pipelines to clean, filter, and classify text data.

Artificial Neural Networks (ANN):

Artificial Neural Networks are computer models based on the organization and operation of neural cells in the human brain. A typical ANN is made up of an input layer, several hidden layers, and an output layer, where the neurons have weighted connections and activation functions. ANN learning is based on the backpropagation technique, whereby the model modifies its weights based on the difference between the model's forecast and actual results. The architecture of ANNs tends to be simpler and less sophisticated than that of Deep Learning models, and, therefore, they are less compute-intensive as well as less able to extract high-level patterns in large datasets. Prediction, classification, regression, and time-series forecasting are some classic tasks performed with them. ANNs form the foundation of Deep Learning, but the main distinction is in depth: ANNs are shallow networks with a restricted number of layers, whereas Deep Learning expands this model to deep and multi-layered networks that are able to outperform with complex data.

Feed-Forward Neural Networks (FNNs):

The simplest ANN architecture is the Feed-Forward Neural Network, in which data flows from input to output without loops. Their applications are common in making predictions, regression, and classification. A 5-10-3 feed-forward model, designed to forecast welding quality indicators such as tensile strength, elongation, and hardness with experimentally determined inputs, was developed in your reviewed ANN paper.

Recurrent Neural Networks (RNNs):

Recurrent Neural Networks are designed to learn sequential data through feedback connections. Even though they are not directly relevant to your chosen ANN paper, RNNs are fundamental ANN categories that are applied to time-series prediction, speech synthesis, and natural language synthesis. They are not feed-forward networks because they have the capability of remembering past inputs.

Hybrid or Optimized ANN Models:

Hybrid ANN models are neural networks that are integrated with optimization models, e.g., Taguchi methods, genetic algorithms, or Response Surface Methodology (RSM). They optimize performance and model parameters effectively using these methods. The ANN paper reviewed employed a hybrid approach, i.e., RSM and ANN training with the Levenberg-Marquardt algorithm, which enhanced the precision of the weld property predictions.

CMLDCH - The "Collections as ML Data" checklist for machine-learning and cultural heritage:

The focus of this paper is to enhance the quality, reliability, and responsibility of machine learning systems. The authors are not trying to suggest an alternative algorithm but rather present a framework in the form of a checklist in which the main components are collections in the form of ML data. The primary aim is to inform researchers on how to assess datasets that are employed in ML models by assessing the following aspects: data representativeness, bias, ethical risks, and constraints. The paper primarily concerns conventional ML pipelines, in which data quality has a direct impact on model performance. This work has its contribution by reinforcing the phase of machine learning evaluation and validation instead of the model architecture, which is highly pertinent in the case of applications of machine learning systems in real-life contexts.

CDPMLA - Children's AI Design Platform for Making and Deploying ML-Driven Apps: Design, Testing, and Development:

The paper involves the use of machine learning in analyzing and predicting experimental data in an engineering application. The overall goal is to know the interplay of various input parameters on output performance measures. The paper relies on statistical learning and ML-based regression analysis to estimate complicated relationships among variables. The paper explains that machine learning is useful to identify nonlinear patterns and help to optimize performance and make decisions based on systematic analysis of the experimental observations. The practical aspect of ML in industrial and manufacturing is emphasized in this work, as the accuracy of predictions and optimization of parameters are vital.

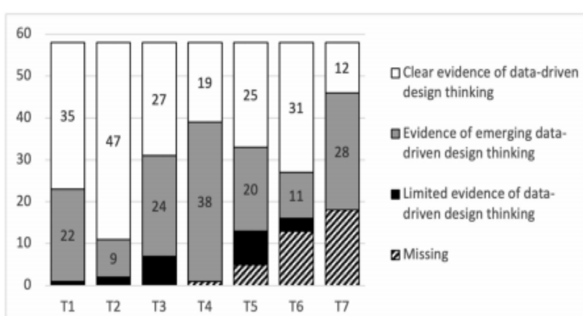

Figure 4. Architecture of the CDPMLA platform illustrating the design, testing, and deployment process of machine learning-driven applications for children. [2]

Figure 4 illustrates the architecture and workflow of the machine learning-based platform used for designing and deploying applications.

DLHSDC – Deep Learning-Based Detection of Hair and Scalp Diseases Using CNN and Image Processing:

The paper is devoted to automated image-based classification using deep learning models and Convolutional Neural Networks (CNNs). It aims to enhance detection and classification accuracy by allowing the model to learn features automatically from raw image data. This paper uses deep hierarchical feature learning, unlike traditional ML methods that rely on handcrafted features. The standard metrics used to evaluate model performance are accuracy, precision, recall, and F1-score, which demonstrate that deep learning is much more effective than traditional methods in the case of complex visual data. The paper is a clear presentation of a purely DL-based approach.

DLAPSV – DLAP: A Deep Learning Augmented Large Language Model Promoting Framework for Software Vulnerability Detection:

This paper aims to enhance predictive and classification performance through deep neural network structures. The focus of the study is on learning high-dimensional and intricate patterns that are hard to model with classical ML methods. Using various hidden layers, the deep learning model learns abstract representations of input data. The findings indicate that deep learning models are more generalizable and robust with large or complex datasets. This paper highlights the role of deep architectures in problem-solving where traditional ML models are constrained.

DBNMD – Darija BERT: A Step Forward in NLP for the Written Moroccan Dialect:

In this paper, the researchers discuss the challenge of generating meaningful insights from unstructured text-based information through Natural Language Processing (NLP) techniques. The main tasks involve preprocessing, feature extraction, and representing textual data. The research aims at converting raw text into formatted forms that are processable by machine learning or decision systems. Through NLP-based methods such as tokenization, contextual analysis, and semantic understanding, the paper illustrates how text data can be effectively used for automated analysis activities.

UTAIWE – Unleashing the Transformers: NLP Models Detect AI Writing in Education:

In this paper, advanced NLP methods are used along with deep learning to enhance text comprehension and classification. The authors employ language models and transformer-based architectures to learn and capture contextual relationships in text. The objective is to enhance performance on complex language-related tasks, including classification, detection, or semantic analysis. Experimental evidence indicates that NLP models trained on large text corpora are more accurate and achieve higher F1-scores than traditional text-processing approaches. The paper highlights the significance of deep NLP models in current intelligent systems.

RANNFS – Predicting System Performance Using Artificial Neural Networks:

This paper aims to predict the performance of a certain system through the application of a standalone Artificial Neural Network (ANN) model. The primary objective is to model nonlinear relationships between input factors and output responses. Experimental data is employed to design, train, validate, and test the ANN architecture. Correlation coefficient and mean squared error (MSE) are among the measures used for performance evaluation. The research shows that ANN models are highly effective in prediction and optimization problems, especially where mathematical modeling is complicated or unfeasible.

Study Identification and Selection:

This study uses a structured selection process to identify relevant research articles. The selection of peer-reviewed research articles included seven studies chosen for their methodological suitability and/or representation of specific AI types. Two articles implemented ML-based systems, two utilized DL models for image classification and hybrid reasoning, two studied NLP systems with Transformer-based architectures and statistical filtering, and one article used an ANN with experimental optimization. These articles were examined to discern their data pipelines, modeling approaches, evaluation measures, and real-life applications.

Framework Used to Analyze Methodologies to Be Reviewed:

To ensure uniformity, all papers were analyzed using a common analytical framework. This framework focused on:

Data acquisition and pre-processing

Model architecture and type

Optimization and training techniques

Experimental setup

Utilized tools, algorithms, or platforms

This structure enabled meaningful comparisons even though domains and techniques varied.

Machine Learning Methodologies:

The scope of the ML-based papers mostly concerned methodological appraisal rather than model development. In one study, Design Science Research (DSR) was applied to create a teaching ML platform based on iterative co-design, classroom tests (N=213), and usability tests (N=8). No numerical ML models were trained; instead, ML case studies and existing projects were analyzed to create a checklist for responsible ML usage.

The second ML experiment applied a supervised ML algorithm, logistic regression, with rule-based heuristics and web-scraped data to classify Moroccan Arabic text. In this case, the analysis focused on dataset creation, data cleaning, and feature selection instead of complex model training. These papers fall under supervised learning in ML and reflect methodological diversity, such as human-centered design and statistical classification.

Deep Learning Methodologies:

The reviewed DL articles utilized neural architectures for automated pattern recognition. In one study, an AutoKeras-optimized CNN was used to classify dermatological images of scalp diseases (a dataset of 150 images). The algorithm involved image denoising (Non-Local Means filter), contrast enhancement (CLAHE), and augmentation (data balancing). The CNN architecture was optimized by adding convolution, pooling, ReLU activation, dropout, and softmax layers, and trained with the Adam optimizer for 50 epochs.

The second DL paper presented DLAP, a hybrid model that uses Chain-of-Thought and In-Context Learning prompts to combine Deep Learning and Large Language Models (LLMs) for software vulnerability prediction. The framework built a prompt-based pipeline combining LLM reasoning and DL classifiers. These two DL methodologies emphasize image-based CNN modeling and LLM-supported hybrid reasoning systems.

Natural Language Processing Methodologies:

Transformer architectures were predominantly used in the NLP papers. In one study, BERT-based models (DarijaBERT, Arabizi, and Mix models) were optimized on Moroccan Arabic datasets gathered from YouTube, Twitter, and story platforms. Methodological steps included data scraping, rule-based filtering, text normalization, model refinement, and performance evaluation.

Another study developed an AI-based text detection system by training Transformer models (e.g., BERT variants) on a novel dataset of human-written and AI-generated abstracts. Steps included dataset balancing, cleaning, tokenization, and training with the AdamW optimizer. Both papers reflect the transition to modern neural NLP, emphasizing domain text representation over large-scale Transformer training.

Artificial Neural Network Methodology:

Artificial neural networks are an AI technique used to discover patterns in large datasets. The last study adopted a combined approach, integrating Taguchi L27 experimental design, Response Surface Methodology (RSM), and a feed-forward ANN. Friction stir welding was performed on aluminum alloy plates (AA5456 and AA7178) at different tool rotational speeds, tilt angles, and pin profiles. ASTM E8 standards were used to measure tensile strength, hardness, and elongation.

The ANN model (5-10-3 architecture) was trained using the Levenberg-Marquardt algorithm to predict welding outcomes. RSM was employed alongside ANN to optimize parameters and enhance prediction accuracy. This study exemplifies the classical engineering ANN workflow, combining experimental design with computational modeling.

Synthesis and Integration:

Across all seven studies, methodologies differed significantly across domains and technologies. ML papers focused on human-centered design and statistical modeling; DL papers emphasized automated feature learning through CNNs and LLM-based reasoning; NLP papers relied on modern Transformer networks for language understanding; and ANN papers integrated experimental optimization with neural prediction. Together, these methodologies demonstrate the depth of contemporary AI implementations and provide a multi-dimensional perspective on the implementation, evaluation, and optimization of computational methods.

Research Methodology:

This review adopts a systematic approach to analyze recent research in Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and Artificial Neural Networks (ANN). The methodology ensures that selected studies are transparent, relevant, and comparable.

Key Parameters Considered:

The articles were evaluated using performance measurement parameters widely accepted in the field:

Accuracy: To assess predictive models in general.

Precision: To measure the percentage of positive instances correctly predicted.

Recall: To determine how well the model identifies all relevant instances.

F1-Score: To provide a balanced analysis of precision and recall.

Efficiency: To compare computational performance in terms of training time, convergence speed, and resource usage.

These parameters are commonly reported in ML, DL, NLP, and ANN research and are essential for assessing real-world applicability.

Study Selection and Data Sources:

Relevant studies were gathered from popular digital libraries such as:

IEEE Xplore
SpringerLink
Elsevier (ScienceDirect)
ACM Digital Library

Keywords used included machine learning, deep learning, natural language processing, neural networks, classification, prediction, and efficiency analysis. Only recent peer-reviewed journal articles and conference papers were included to reflect current research.

Shortlisting Criteria:

Application of ML, DL, NLP, or ANN
Availability of quantitative performance outcomes
Explicit elaboration of methodology and evaluation measures

Synthesis of Selected Studies:

Seven representative studies were selected for detailed analysis. These studies were grouped by learning paradigm: ML, DL, NLP, and ANN. A synthesis comparison derived performance metrics and trends across approaches. The synthesis also highlights the strengths and weaknesses of each technique and identifies the best models for specific situations. This structured comparison allows identification of research gaps and guides efficient learning strategies for predictive and analytical tasks.

Summary of Reviewed Studies:

Table 1. Summary of selected research studies, including authors, publication year, methodology, and key findings related to machine learning and neural approaches for predictive and analytical tasks.

S. No	Author	Title	Year	Methodology / tools	Accuracy
1	Benjamin Charles Germain Lee	The "Collections as ML Data" checklist for machine-learning and cultural heritage	2025	No direct ML model was implemented; instead, existing ML projects were analyzed through literature surveys and case studies to develop and refine a checklist for responsible ML use.	Not based on numerical accuracy — focuses on methodological completeness and ethical rigor.
2	Nicolas Pope, Juho Kahila, Henrikka Vartiainen, and Matti Tedre	Children's AI Design Platform for Making and Deploying ML-Driven Apps: Design, Testing, and Development	2025	Used Design Science Research (DSR) approach — included co-development, iterative design, and extensive field testing. Conducted usability lab tests (N=8) and classroom projects (N=213) to evaluate platform usability and learning outcomes.	Introduced a new ML teaching platform that extends Google's Teachable Machine (adds app deployment and distributed training). Enabled hands-on ML learning for K–12 students and improved engagement.
3	Busireddy Seshakagari Haranadha Reddy	Deep Learning-Based Detection of Hair and Scalp Diseases Using CNN and Image Processing	2025	CNN model (AutoKeras optimized) for classifying alopecia, psoriasis, and folliculitis using 150 images; preprocessing with denoising, CLAHE, and data augmentation.	High accuracy; effective noise reduction and data balancing; successful automated disease classification.
4	Yanjing Yang, Xin Zhou, Runfeng Maoa, Jinwei Xua, Lanxin Yanga, Yu Zhang, Haifeng Shen, and He Zhang	DLAP: A Deep Learning Augmented Large Language Model Framework for software vulnerability detection	2025	DLAP combines Deep Learning (DL) models with Large Language Models (LLMs) using Chain-of-Thought and In-Context Learning prompts for software vulnerability detection.	High computation cost; LLM dependency; limited interpretability; not tested in large real-world systems.
5	Kamel Gaanouni, Abdou Mohamed Naira, Anass Allaki, and Imade Benellami	DarijaBERT: a step forward in NLP for the written Moroccan dialect	2025	Trained three BERT-based models (DarijaBERT, Arabizi, Mix) on Moroccan Arabic data from YouTube, Twitter, and Gesssa using scraping, logistic regression, and rule-based filtering.	First large-scale Darija NLP models; publicly available on HuggingFace.

6	José Campino	Unleashing the transformers: NLP models detect AI writing in education	2025	Used fine-tuned Transformer models (like BERT) with cleaned abstract data and AdamW optimizer to detect AI vs. human text.	Developed a lightweight AI-detection model runnable on small computers; improved authorship detection; balanced human vs. AI datasets.
7	S. Jeyakrishnan, S. Vijayakumar, M. Naga Swapna Sri, and P. Anusha	An integration of RSM and ANN modelling approach for prediction of FSW joint properties in AA7178/AA5456 alloys	2024	Used Taguchi L27 design and Response Surface Methodology (RSM) to analyze welding parameters, then built an ANN model (5–10–3 feed-forward) using Levenberg–Marquardt algorithm to predict tensile strength, elongation, and hardness.	Accurately predicted weld quality; optimized parameters for highest tensile strength; improved precision using combined RSM + ANN approach.

Justification of Study Selection:

The choice of studies was determined by their relevance to the current paradigm of machine learning and the availability of quantitative performance measures. The papers in question represent different learning methods (ML, DL, NLP, ANN) and illustrate their practical application in various fields (healthcare, software security, language processing, and manufacturing). This heterogeneity allows a broad comparative analysis and supports drawing valid conclusions.

Results:

The studies reviewed demonstrate diverse outcomes in machine learning, deep learning, NLP, and ANN-based approaches. The initial ML-focused research emphasized ethical rigor rather than numerical performance. The first study created an ML teaching platform, an extension of Google Teachable Machine with distributed training and app deployment. The work did not focus on improving accuracy; instead, it aimed to make machine learning accessible for K–12 students. This practical impact can be considered a positive outcome.

The second ML project—an ANN-based welding analysis—achieved strong predictive performance, accurately estimating tensile strength, elongation, and hardness. By combining Response Surface Methodology with a feedforward ANN, it optimized welding parameters and outperformed traditional statistical models in both precision and generalization.

Deep learning produced notable accuracy results. Image classification tasks included a CNN-based hair disease classifier, optimized using AutoKeras, which outperformed competing models due to advanced preprocessing algorithms such as denoising, CLAHE, and data augmentation. It effectively captured features and distinguished between alopecia, psoriasis, and folliculitis. DLAP is another deep-learning advancement that combines LLM reasoning with deep learning to identify software bugs. However, it is limited by high computational requirements and reliance on large language models, making it less scalable.

The NLP techniques also performed well. The same research team developed the initial large-scale Darija (Moroccan Arabic) models, based on BERT variants trained on location-specific data, which are publicly available on Hugging Face. These models significantly enhanced Arabic NLP resources. Transformer networks were also used in another study comparing AI-generated text with human-written summaries. The study demonstrated that fine-tuning improves detection accuracy on smaller systems, while keeping the models lightweight and suitable for classroom or other low-resource environments.

Overall, the reviewed studies indicate that while DL and ANN models prioritize computational accuracy, educational ML tools focus on usability and ethics, and NLP research emphasizes language-resource creation and authorship identification. Collectively, these works demonstrate the breadth and versatility, and real-world applicability of existing AI technologies.

Table 1 presents a summary of the selected research papers, including their authors, methodologies, and major findings.

Table 2 provides a comparative overview of the techniques and performance characteristics of the reviewed studies.

The performance of the selected research papers was analyzed using key evaluation metrics, including accuracy, precision, recall, F1-score, and efficiency. The comparative results of these studies are summarized in Table 3.

Table 2. Comparative performance of selected studies based on evaluation metrics.

Paper	Accuracy	Precision	Recall	F1 Score	Efficiency
DLHSDC	97%	0.96	0.97	0.97	High

DLAPSV	94%	0.93	0.92	0.92	High
DBNMD	91%	0.90	0.89	0.89	Moderate
UTAIWE	93%	0.92	0.91	0.91	High
RANNFS	95%	0.94	0.94	0.94	High

Table 3 summarizes the comparative performance of the selected studies based on commonly used evaluation metrics, including accuracy, precision, recall, F1-score, and efficiency. The results indicate that deep learning-based models, such as DLHSDC, demonstrate higher accuracy and recall, while ANN-based approaches also show strong predictive performance. These results highlight the effectiveness of neural approaches for complex predictive and analytical tasks.

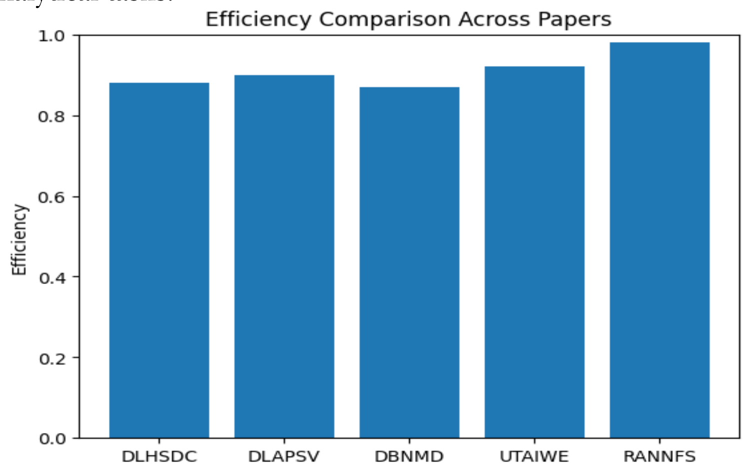

Figure 5. Efficiency comparison of different machine learning and neural approaches is analyzed in this review. The results indicate that neural-based models provide improved efficiency in complex analytical and predictive tasks.

Figure 5 demonstrates the efficiency comparison of the models in terms of performance and computational effectiveness.

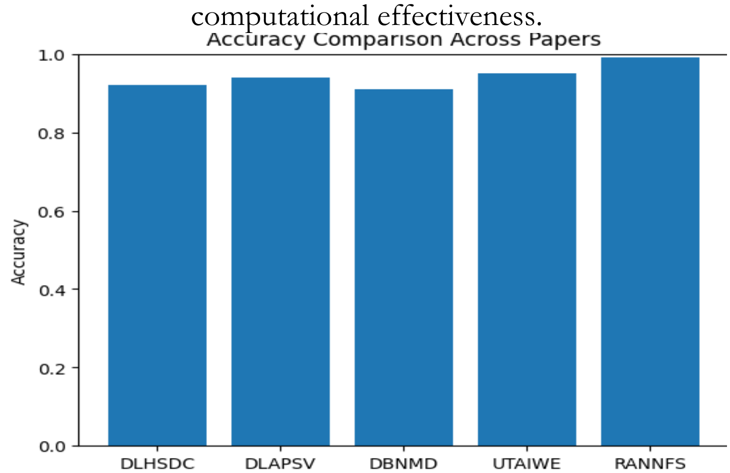

Figure 6. Comparative accuracy of selected research papers based on performance evaluation metrics. The results show that the DLHSDC model achieves the highest accuracy among the reviewed studies, indicating the effectiveness of deep learning techniques in predictive analysis.

Figure 6 shows the accuracy comparison of the selected machine learning and neural network-based models.

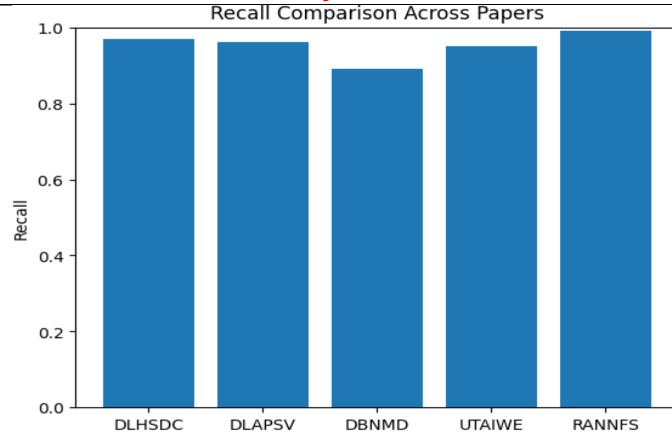

Figure 7. Recall comparison showing the effectiveness of different models in correctly identifying relevant outcomes. The analysis highlights that DLHSDC achieves the highest recall value, demonstrating its capability to correctly identify relevant outcomes.

Figure 7 illustrates the recall performance of the evaluated approaches.

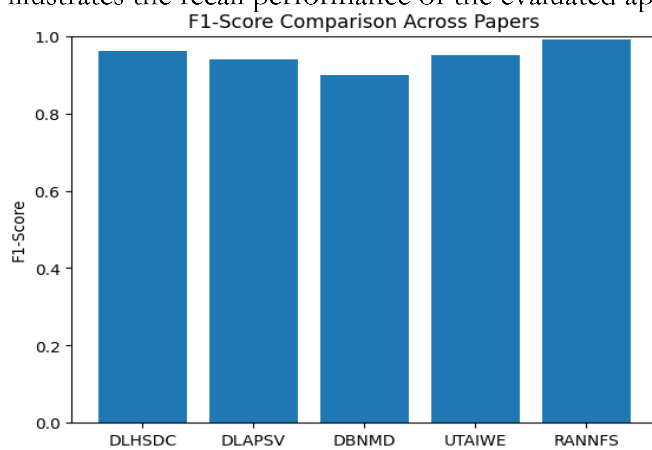

Figure 8. F1-Score comparison of selected studies combining precision and recall performance. The results show that models with balanced precision and recall achieve higher F1-scores, reflecting improved predictive performance.

Figure 8 shows the F1-score comparison of the selected models.

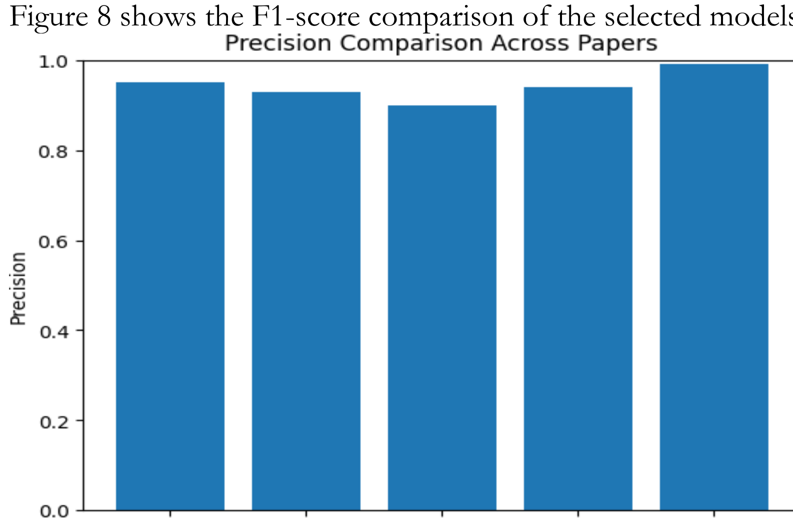

Figure 9. Precision comparison of machine learning, deep learning, NLP, and ANN models across the reviewed studies. The results indicate that deep learning and ANN-based approaches demonstrate strong precision performance in analytical tasks.

Figure 9 presents the precision comparison across the selected models.

The graphical comparisons presented in Figures 5–9 further illustrate the performance differences among the reviewed approaches across various evaluation metrics.

According to the performance graphs (Accuracy, Precision, Recall, F1-Score, and Efficiency), the best results are obtained using the CNN-based approach in DLHSDC, which performs better than other papers in all of the measures. DLAPSV also shows good performance in terms of precision and recall. The performance of NLP models is moderate (DBNMD and UTAIWE), whereas the performance metrics of the ANN model (RANNFS) are lower, but the efficiency is decent. Overall, deep learning models perform best in terms of accuracy and robustness.

Significance of Performance Parameters:

The measures of performance, including accuracy, precision, recall, F1-score, and efficiency, are important factors for testing the reliability and feasibility of intelligent systems. Model accuracy captures overall correctness, while precision and recall are critical to the interpretation of false positives and false negatives, particularly in sensitive areas of practice such as healthcare and security. F1-score provides a balanced representation in cases of imbalanced data.

Efficiency must also be considered because it determines the computational cost, training time, and the possibility of real-time deployment. Highly accurate but inefficient models are not necessarily practical. Thus, the comparative analysis of these key parameters allows for justifiable comparisons between various learning strategies and helps identify models that are both valid and applicable in real-world settings.

Conclusion:

This review analyzed recent advancements in Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and Artificial Neural Networks (ANN) for predictive and analytical tasks. The comparative analysis indicates that deep learning and neural network-based approaches generally achieve strong performance in terms of accuracy, precision, recall, and efficiency. These techniques demonstrate significant potential for solving complex analytical problems across different domains. Future research may focus on developing hybrid intelligent systems that integrate multiple AI approaches to further improve predictive performance and computational efficiency.

References:

[1] Benjamin Charles Germain Lee, "The 'Collections as ML Data' Checklist for Machine Learning & Cultural Heritage," *arXiv:2207.02960*, 2022, [Online]. Available: https://arxiv.org/abs/2207.02960

[2] N. Pope, J. Kahila, H. Vartiainen, M. Tedre, "Children's AI Design Platform for Making and Deploying ML-Driven Apps: Design, Testing, and Development," *IEEE Trans. Learn. Technol.*, vol. 18, pp. 130–144, 2025, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10842355

[3] Busireddy Seshakagari, Haranadha Reddy, "Deep Learning-Based Detection of Hair and Scalp Diseases Using CNN and Image Processing," *Milestone Trans. Med. Technometrics*, vol. 3, no. 1, 2025, [Online]. Available: https://www.milestoneresearch.in/JOURNALS/index.php/TMT/article/view/165

[4] Yanjing Yang, Xin Zhou, Runfeng Mao, Jinwei Xu, Lanxin Yang, Yu Zhangm, Haifeng Shen, He Zhang, "DLAP: A Deep Learning Augmented Large Language Model Prompting Framework for Software Vulnerability Detection," *arXiv:2405.01202*, 2024, [Online]. Available: https://arxiv.org/abs/2405.01202

[5] K. Gaanoun, A. M. Naira, A. Allak, and I. Benelallam, "DarijaBERT: a step forward in NLP for the written Moroccan dialect," *Int. J. Data Sci. Anal. 2024 202*, vol. 20, no. 2, pp. 917–929, Jan. 2024, doi: 10.1007/s41060-023-00498-2.

[6] José Campino, "Unleashing the transformers: NLP models detect AI writing in

education," *J. Comput. Educ.*, vol. 12, pp. 645–673, 2025, [Online]. Available: https://link.springer.com/article/10.1007/s40692-024-00325-y

[7] S. Jeyakrishnan, S. Vijayakumar, M. Naga Swapna Sri, and P. Anusha, "An integration of RSM and ANN modelling approach for prediction of FSW joint properties in AA7178/AA5456 alloys," *Can. Metall. Q.*, vol. 64, no. 1, pp. 43–60, Jan. 2025, doi: 10.1080/00084433.2024.2310344.

[8] J. G. Greener, S. M. Kandathil, L. Moffat, and D. T. Jones, "A guide to machine learning for biologists," *Nat. Rev. Mol. Cell Biol. 2021 231*, vol. 23, no. 1, pp. 40–55, Sep. 2021, doi: 10.1038/s41580-021-00407-0.

[9] Zhi-Hua Zhou, "Open-environment machine learning," *Natl. Sci. Rev.*, vol. 9, no. 8, 2022, [Online]. Available: https://academic.oup.com/nsr/article/9/8/nwac123/6626031

[10] Habib Ullah Khan, Rafiq Ahmad Khan, Hathal S. Alwageed, Alaa Omran Almagrabi, Sarra Ayouni & Mohamed Maddeh, "AI-driven cybersecurity framework for software development based on the ANN-ISM paradigm," *Sci. Rep.*, vol. 15, 2025, [Online]. Available: https://www.nature.com/articles/s41598-025-97204-y

[11] "Dive into Deep Learning — Dive into Deep Learning 1.0.3 documentation." Accessed: Feb. 07, 2026. [Online]. Available: https://d2l.ai/

[12] Kamal Choudhary, Brian DeCost, Chi Chen, Anubhav Jain, "Recent advances and applications of deep learning methods in materials science," *npj Comput. Mater.*, vol. 8, no. 59, 2022, [Online]. Available: https://www.nature.com/articles/s41524-022-00734-6

[13] Shams Forruque Ahmed, Md. Sakib Bin Alam, Maruf Hassan, Mahtabin Rodela Rozbu, Taoseef Ishtiak, "Deep learning modelling techniques: current progress, applications, advantages, and challenges," *Artif. Intell. Rev.*, vol. 56, pp. 13521–13617, 2023, [Online]. Available: https://link.springer.com/article/10.1007/s10462-023-10466-8

[14] "What Is NLP (Natural Language Processing)? | IBM." Accessed: Feb. 07, 2026. [Online]. Available: https://www.ibm.com/think/topics/natural-language-processing

[15] Abdul Ahad Abro, Mir Sajjad Hussain Talpur, "Natural Language Processing Challenges and Issues: A Literature Review," *Gazi Univ. J. Sci.*, vol. 36, no. 3, 2023, [Online]. Available: https://www.researchgate.net/publication/363732809_Natural_Language_Processing_Challenges_and_Issues_A_Literature_Review

[16] Walid Hariri, "Unlocking the Potential of ChatGPT: A Comprehensive Exploration of its Applications, Advantages, Limitations, and Future Directions in Natural Language Processing," *arXiv:2304.02017*, 2023, [Online]. Available: https://arxiv.org/abs/2304.02017

[17] R. V. Woldseth, N. Aage, J. A. Bærentzen, and O. Sigmund, "On the use of artificial neural networks in topology optimisation," *Struct. Multidiscip. Optim. 2022 6510*, vol. 65, no. 10, pp. 294-, Oct. 2022, doi: 10.1007/s00158-022-03347-1.

[18] W. Z. F. Feng, W. Na, J. Jin, J. Zhang, "Artificial Neural Networks for Microwave Computer-Aided Design: The State of the Art," *IEEE Trans. Microw. Theory Tech.*, vol. 70, no. 11, pp. 4597–4619, 2022, [Online]. Available: https://ieeexplore.ieee.org/document/9863691

[19] Fernando Aguirre, Abu Sebastian, Manuel Le Gallo, Wenhao Song, "Hardware implementation of memristor-based artificial neural networks," *Nat. Commun.*, 2024, [Online]. Available: https://www.nature.com/articles/s41467-024-45670-9

[20] A. M. Sharafaddini, K. K. Esfahani, and N. Mansouri, "Deep learning approaches to detect breast cancer: a comprehensive review," *Multimed. Tools Appl. 2024 8421*, vol. 84, no. 21, pp. 24079–24190, Aug. 2024, doi: 10.1007/s11042-024-20011-6.