Library Progress International *Print version ISSN 0970 1052*
Vol.44 No. 3, Jul-Dec 2024: P.10806-10816 *Online version ISSN 2320 317X*

Original Article *Available online at www.bpasjournals.com*

Comparative Insights into Machine Learning and Deep Learning Models: Applications and Performance

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How to cite this article: Sarabjit Kaur, Nirvair Neeru (2024) Comparative Insights into Machine Learning and Deep Learning Models: Applications and Performance. *Library Progress International*, 44(3), 10806-10816

ABSTRACT

This paper compares ML and DL, two key areas of AI, to understand their strengths and weaknesses and facilitate model selection for different applications. ML includes approaches such as DT and SVM, which are suitable for smaller datasets and simpler tasks, while DL uses neural networks to tackle large datasets and complex tasks such as image detection & NLP. We evaluate their performance based on accuracy, speed and interpretability. We find that ML models are often faster and easier to understand, while DL models excel in accuracy for complex problems. Practical applications in industries like healthcare, finance & retail are examined, demonstrating the effectiveness of ML on predictive tasks and the superiority of DL on tasks requiring detailed data analysis. This study provides insights to help scholars select the appropriate AI models for particular demands and thus improve the application of AI in solving real-world challenges.

Keywords: AI, ML, Deep Learning, Comparative Analysis, Model Performance, Predictive Analysis.

I.OVERVIEW OF AI AND ITS SUBSETS

The phrase AI refers to the ability of technology, particularly computer systems, to mimic human intellectual functions. These steps include learning how to acquire data, apply it according to rules, or self-correct. They also involve reasoning using rules to arrive at approximations or firm conclusions. AI is a general tem for a scale of methods and technology aimed at building devices that could carry out tasks that would typically need human intelligence, like speech detection, visual perception, language translation, and decision making [1].

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ML is the field which focuses on creating approaches & statistical designs that enable machines carry out specific duties without direct guidance. Instead, ML systems learn from information & make predictions or decisions depend on data.

DL is a sub-area of ML that involves neural networks with many layers that can learn from large quantity of information. DL approaches including CNNs & RNNs, are particularly effective at processing and analyzing complex information like images & audio. The ability of DL to automatically recognize features and its success in processing large set of information has led to its widespread use in various fields.

A. Differences between ML and DL

Understanding the differences among ML & DL is crucial for both researchers and practitioners. These technologies, while related, have distinct characteristics, capabilities, and limitations. By comprehending these differences, individuals and organizations can make informed decisions about which approach to use based on their specific needs and constraints.

Different tasks and datasets may be better suited to ML or DL techniques. For example, ML algorithms might be preferred for simpler tasks or smaller datasets due to their lower computational requirements and better interpretability. On the other hand, DL models excel in handling large, complex datasets and tasks that involve high-dimensional data. Understanding these nuances helps in selecting the right design for a given issue, optimizing performance, and resource utilization.

ML and DL models differ greatly in how well they perform, how fast they are, and how much resources they use. DL models usually perform better in complicated tasks but need more computing power and longer training times [2]. Understanding these trade-offs helps in planning and managing resources, especially when time and computing power are limited.

This main aim of the paper is to compare ML and deep learning models in detail. It looks at performance, computational needs, how easy the models are to understand, how well they scale, and how flexible they are. The aim is to show where each type of model works best and where it might not perform as well.

II. LITERATURE SURVEY

ML and DL are two branches of AI that have attracted a lot of attention recently. The method of developing predictive models is made easier by a method of data analysis known as machine learning. It enables machines to learn and grow independently without requiring human programming. But deep learning (DL) is a subfield of machine learning that uses neural networks to solve difficult problems. Because DL algorithms are inspired by the structure and operation of the human brain, they are able to derive information from unstructured and unlabeled data.

Treesukon Treebupachatsakul et al.(2020) ML & DL are two branches of AI that have attracted a lot of attention recently. The process of developing predictive models is made easier by a method of data analysis known as machine learning. It enables systems to gain knowledge and develop independently without requiring human programming. Moeover, DL investigates the potential for using DL techniques and image classification to identify bacteria and yeast using a comparison of the quality of cell image data across our high-resolution and standard-resolution datasets. Researchers use the Keras API in conjunction with the Tensorflow ML structure, together with Python programming, to construct this method of microbe recognition. The results of this study have demonstrated the ability to identify bacteria and yeast cells from microscope images. According to studies comparing deep learning methods with various quality picture datasets, proposed standard resolution dataset may be used to predict bacteria and yeast with an accuracy of over 80%[7].

Jain et al.(2020) Two areas of AI that have received a lot of interest lately are ML and DL. An approach to data analysis called ML simplifies the process of creating analytical models. It makes it possible for computers to grow and learn on their own without needing to be manually programmed. However, DL uses SS D and Faster RCNN methods, which are based on CNNs, to accomplish automatic gun (or) weapon detection. Two kinds of information are used in the suggested solution. There was one dataset with pre-identified photos and another with a collection of manually labeled images. The SSD approach offers a higher rate of 0.736 s/frame. On the other hand, SSD outperforms quicker RCNN, which only manages 1.606 s/frame. Higher precision is achieved using quicker RCNN, which scores 84.6%. By comparison, SSD only offers 73.8% accuracy, which is not as good as RCNN's speed. SSD's quicker speed allowed for immediate recogntion, but Faster RCNN's higher accuracy was maintained [8].

Chaiwat Sirawattananon et al.(2021) suggested a DL-based robotic automation system to assist in ensuring suitable trash classification in the recycling divisions. The ResNet-50 has been used to classify the trash. The system was trained using the TrashNet database in addition to a local image set consisting of about 5,326 images of four different rubbish types. 98.81% of the analysis was accurate[9].

Kadir Sabanci et al.(2021) Inside locations where the user was unable to accurately receive the GPS signal, a location determination determined by WiFi signal strength was carried out. The information contains the potencies of 7 WiFi signals that offer details about 4 distinct rooms. The WiFi signal strength measurements that the Smartphone receives from 7 different sources can be used to determine the user's position across every room. In this study, the indoor room was identified using classification. The ANN,k-NN, SVM, DT, NB Classifier, and ELM are these techniques. All of the strategies produced successful outcomes, which were then compared to one another [10].

Hossain et al.(2018) provided a productive DL structure for classifying fruits. More precisely, two distinct DL deep learning serve as the foundation for the system. A suggested light system consisting of six CNN layers is shown in the first, and an improved visual geometry group-16 pre-trained DL design is presented in the second. We test the proposed structure on two color-image databases, one of which is accessible to everyone. There are unambiguous fruit photos in the first dataset (dataset 1) and difficult-to-classify fruit images in the second database (database 2). On dataset 1, the first & second classifiers attained classification accuracies of 99.49% and 99.75%, respectively. The first & second designs achieved accuracy of 85.43% and 96.75%, respectively, on database 2[11].

Mark Barnell et al.(2023) entailed using sensor data representative of sources of information from a small research stage to train spiking neural networks (SNN). In our approach, researchers employ ML to forecast the platform mode based on representative sensor data. Most importantly, we successfully scaled from IBM's TrueNorth Corelet structure to Intel's Loihi 2 neuromorphic processor's Lava architecture rapidly. The Lava framework is used to exhibit capabilities on small aerial platform sensor information that is vast extensible to other domains that could employ this neuromorphic computation hardware demonstrating the state-of-the-art in edge computing. To summarize, this study employed innovative processing computations, new computational structures, and a distinct operational concept. With up to 97.6% accuracy, the system's mode was classified using this technical method based on the sensor data[12].

Dhivya Elavarasan et al.(2020) builds a DRQN framework to anticipate crop yield, which is a DL approach based on RNN over Q-Learning reinforcement learning algorithm. The data variables feed the RNN successively stacked levels. Based on the input parameters, the Q-learning system builds a crop yield prediction environment. The output values of the RNN are mapped to the Q-values via a linear layer. To help anticipate crop productivity, the RL agent merges a set of parametric features with the threshold. Ultimately, by minimizing mistake and improving forecast accuracy, the agent's actions result in an overall score. The proposed approach outperforms earlier models in crop yield forecasting, with an accuracy of 93.7%[13]. It does this while maintaining the original data distribution.

Hina Tufail et al., (2022) proposed a fake review recognition design by using Text Classification & approaches related to ML. We used classifiers like SVM, KNN using a bigram design that identifies fraudulent reviews depend on the set of pronouns, verbs, sentiments. In comparison to other cutting-edge methods, suggested approach for identifying phony internet reviews works better on the Yelp and TripAdvisor datasets, with 95% or 89.03% accuracy, respectively[14].

Muhammad Saad Javed et al., (2021) several alternative methods for collecting behavioral or non-textual data, as well as a suggested CNN-based structure for collecting textual data. Ensemble methods were used to integrate 3 models. The	**Objective**	**Technique**	**DAtaset**	**Drawbacks**	**Conclusion**

Yelp filtered dataste utilized in this study removes fraudulent reviews using an algorithm. According to the studies, meaningful information that might be integrated in multiple ways to enhance each other and improve accuracy is extracted utilizing parallel convolution blocks. The ensemble method outperforms state-of-the-art methods by up to 7%, yielding an accuracy of 92.42% with an average recall of 92.14% on the restaurant domain as well as an accuracy of 91.66% with an average recall of 91.67% on the hotel domain. This research demonstrates the efficacy of large convolutional technique and ensemble methods in NLP[15].**Table I: Comparative Analysis of Existing workAuthor's Name/Year**					

Jain et al.(2020)	Weapon detection	convolution neural network (CNN)	Fatkun Batch Image Downloader (chrome extension)	Unable to work on larger datasets.	SSD's quicker rate allowed for immediate identification, but Faster RCNN's higher accuracy of 84.6% was achieved.
Chaiwat Sirawattananon et al.(2021)	Make sure the waste is properly separated into its recycling groups.	deep learning techniques	TrashNet	-	The experimental accuracy was 98.81%.
Mark Barnell et al.(2023)	SNN generation using relevant data from sensors.	Deep Learning	IBM's TrueNorth Corelet	small airborne platform sensor data	Platform state identification with up to 97.6% accuracy based on sensor data.
Hina Tufail et al., (2022)	Fake Reviews Detection	Machine Learning	Twenty Yelp.com or TripAdvisor assessments of hotels	Not to delve deeply into the semi-supervised field of Positive-unlabeled (PU) learning approaches.	The findings demonstrate that SKL-based fake reviews have an accuracy of 95% on Yelp datasets and 89.03% on TripAdvisor datasets.
Muhammad Saad Javed et al., (2021	Fake reviews classification	Multi-view learning	Yelp Filtered Dataset	-	Suggested approach achieves F1 scores of up to 92%
Dhivya Elavarasan et al.(2020)	Crop yield prediction	RNN- DL approach	Paddy crop for the Vellore district	-	Accuracy =93.7%

III. MACHINE LEARNING ALGORITHMS

The investigation and utilization of systems that improve on their own with practice or increased data usage is known as ML. It is a way to analyze data that automates the creation of models, letting systems find patterns and insights in data without being directly programmed to do so [3].

A. Types of ML

Supervised learning, unsupervised learning, semi-supervised learning, or reinforcement learning are the four primary categories into which ML can be separated [4].

In supervised learning, a database with labels is utilized to train a design, with a result name assigned to each instance. The model learns from these input-output pairs to make predictions or decisions. After training, it can predict outputs for new, unseen inputs. Examples include LR, SVM, and decision trees.

A model that is trained using unlabeled response information in unsupervised learning. The model tries to find patterns and structures in the data without knowing the output. It identifies hidden designs within the input information. Common examples include K-means clustering, hierarchical clustering, and PCA. These methods are important for tasks where data labels are missing or hard to obtain, enabling the discovery of underlying patterns and insights in datasets.

To enhance learning, semi-supervised learning combines a greater quantity of unlabeled input with a lesser amount of labeled data. This approach is useful when labeled data is expensive or hard to obtain. By using additional unlabeled data, the model can better understand the patterns in the dataset.

Reinforcement learning, on the other hand, trains an agent through trial-and-error interactions with an environment. The agent learns to achieve specific goals by getting rewards for good actions and penalties for bad ones. Over time, this feedback helps the agent improve its decision-making and behavior, making it effective in dynamic environments and complex tasks.

B. Common ML Algorithms

Table 1 presents a clear comparison of common ML algorithms, categorizing them into supervised and unsupervised types, and outlining their use cases, strengths, and weaknesses.

Table 1I: Comparison of ML AppoachesAlgorithm	**Type**	**Use Case**	**Advantages**	**Disadvantages**
Linear Regression	Supervised	Forecasting constant values	Simple & easy to comprehend	Based on a linear connection and is outlier susceptible
Logistic Regression	Supervised	Binary classification	provides understandable options	A decision boundary that is flat
DT	Supervised	Classification, regression	Intelligible and able to handle non-linear relationships	vulnerable to deep tree over-fitting
RF	Supervised	Classification, regression	reduces overfitting and effectively handles massive data sets	More complex to understand as well as costly to compute than DT
SVM	Supervised	Classification, regression	Adaptable kernel with high-dimensional spatial success	memory-intensive; precise selection of variables or kernel functions is required
KNN	Supervised	Classification, regression	It is simple to use, needs little training, and handles complex decision boundaries.	sensitive to trivial details and expensive to compute during inference
NB	Supervised	Classification, text mining	Rapid and efficient for managing vast amounts of data	implies that the qualities are independent of one another
K-Means Clustering	Unsupervised	Clustering	Fast, simple, and capable of managing	Outlier sensitivity requires the total

			large datasets	number of clusters to be specified in advance.
Hierarchical Clustering	Unsupervised	Clustering	Displays an adaptable hierarchical arrangement	Costly to compute for huge datasets
PCA	Unsupervised	Dimensionality reduction	minimizes dimensionality while preserving the most crucial elements	implies that the relationships among variables are linear
Apriori	Unsupervised	Association rule learning	finds common items in transactional data	rigid in controlling outliers & noise, as well as requiring a lot of memory for huge data sets

Every method's comprehension, computational effectiveness, risk of over fitting or under fitting, and its ability to handle specific information types are evaluated. Understanding these aspects is essential for information scientists and practitioners to select the most appropriate algorithm for a task or dataset. By considering the pros and cons listed, stakeholders can make informed choices to enhance model performance and tackle real-world issues in fields like finance, healthcare, and marketing.

IV. DEEP LEARNING ALGORITHMS

DL is a subfield of ML that models complicated information patterns by employing neural networks [5]. The architecture and operation of the human brain, in particular the relationships among neurons, served as the model for these DL methods.

Several key characteristics set DL models apart from traditional machine learning approaches. First, DL models excel at hierarchical feature learning, automatically extracting more abstract features from raw data through multiple layers. This is especially useful for tasks involving complex data like images and speech. However, DL models typically require large datasets to conduct well, relying on substantial amounts of data. The training process for DL models can also be computationally intensive, often requiring specialized hardware like GPUs to efficiently handle the complex computations.

Another significant feature of DL is its end-to-end learning capability, allowing models to learn directly from raw data without extensive manual feature engineering, which simplifies the development process. Despite these advantages, DL models are often seen as black boxes due to their complex structures and internal workings, making it difficult to understand how they make specific decisions compared to more transparent traditional ML models.

A. Types of DL Algorithms

Table 2 offers a comparative summary of various deep learning frameworks [6], each designed to tackle specific challenges and tasks in AI.**Table III: Comparison of Types of DL Algorithms**

Type	Description	Applications	Examples
CNNs	Intended to process photos and other structured grid information. Convolutional layers are used by them to learn spatial relationships and extract	Image recognition, object detection, video analysis	AlexNet, VGG, ResNet

	information.		
Recurrent Neural Networks (RNNs)	Suitable for sequential infomation where the current output depends on previous computations. They have memory to process sequences.	Natural language processing, speech recognition	LSTM, GRU
LSTMs	Specialized RNNs capable of learning long-term dependencies. They maintain a cell state to capture sequential patterns effectively.	Speech recognition, text generation, time series prediction	LSTM
GANs	consists of two neural networks that compete with one another ,a discriminator and a generator to produce data that is realistic.	Image generation, video generation, data augmentation	DCGAN, CycleGAN
Autoencoders	Neural networks are computers with the ability to rebuild output from a lower-dimensional approximation created by encoding input data.	Data compression, feature learning, anomaly detection	Variational Autoencoders (VAEs), Sparse Autoencoders

Grasping the differences between these DL frameworks is essential for choosing the best approach for specific AI tasks. Each type has unique strengths and benefits, but also involves factors like computational complexity, data needs, and interpretability. These considerations are vital for creating effective AI solutions.

V. PERFORMANCE METRICS AND EVALUATION CRITERIA

A. Performance Metrics

Performance metrics are crucial for evaluating how well ML designs work. They measure the design's effectiveness on a specific task, including factors such as accuracy, precision, recall, F1 score, ROC-AUC, and specialized metrics for specific apps, such as the BLEU score for natural language processing (NLP).

Accuracy: The percentage of instances correctly classified relative to all instances is called as accuracy.

Precision: The precision of a forecast is the ratio of precise positive forecasts to all positive forecasts.

Recall (Sensitivity): Recall quantifies the proportion of true positive cases that the equation correctly predicted.

F1 Score: recall and accuracy in the harmonic mean, which offers a fair measure of each.

ROC-AUC: It gauges the model's capacity to discriminate across classes, which is especially helpful for jobs involving binary classification.

Specialized Metrics: Depending on the application, specialized metrics like BLEU score for evaluating the quality of machine-translated text in NLP are used.

B. Computational Complexity

Computational complexity refers to the resources and time required to train and run ML models, including both hardware and software dependencies.**Table IV. Description and Examples of Metrics Metric**	**Description**	**Examples**
Training Time	Time taken to train the design on a database.	Hours, days, or weeks depending on dataset size and design complexity.
Inference Time	Time taken to predict	Milliseconds to seconds,

	outputs once the model is trained.	depending on model architecture and hardware.
Resource Requirements	Hardware and software resources needed for training and inference.	GPUs, TPUs, memory, and CPU requirements.

C. Model Interpretability

Model interpretability is about understanding how a model makes predictions. It's important because it assists us see why a model decides certain things, making decision-making clear and transparent. Models like decision trees and linear models are easier to understand because their decisions are straightforward.

Approaches like SHAP (Shapley Additive explanations) values and LIME (Local Interpretable Model-agnostic Explanations) help explain black-box models. They approximate how these designs work either locally or across the board, making their

D. Scalability and Flexibility

Scalability and flexibility describe how well a design can manage huge amounts of data and adjust to different tasks and settings. It's crucial for models to handle large datasets effectively without sacrificing performance or needing excessive computing power. They also need to be adaptable across various tasks and fields, capable of adjusting their settings and learning from different patterns as needed.

E. Application Suitability

Application suitability evaluates how well different ML designs meet the requirements of specific problem types and industries.

Table V: Application Suitability of Machine Learning Models across IndustriesProblem Type	Industry	Comparative Advantages	Limitations
Classification	Healthcare	High accuracy in predicting diseases from medical images	Requires huge labeled datasets for training
Regression	Finance	Predicting stock prices with high precision	Vulnerable to market volatility
Clustering	Retail	Segmenting customer groups for targeted marketing	Sensitivity to noisy data
Anomaly Detection	Cybersecurity	Detecting unusual network activity	Difficulty in defining normal behavior

Knowing these metrics and standards is crucial for choosing the right machine learning model and assessment techniques to guarantee the best performance and suitability for different real-life situations and industries.

VI. CONCLUSION

The conclusion provides a comprehensive overview of the paper's exploration and comparison of ML & DL designs, emphasizing their applications and performance metrics. It begins with an introduction to AI and its subsets, distinguishing ML's interpretability and DL's prowess in learning hierarchical data representations. Detailed discussions cover common ML algorithms and various types of DL structures tailored for specific tasks like image detection and NLP. The importance of performance metrics, computational complexity, model interpretability tools, and application suitability across industries such as healthcare and finance is highlighted. Overall, the conclusion underscores the paper's role in guiding practitioners and researchers in leveraging ML and

DL effectively to address diverse challenges and foster advancements in artificial intelligence.

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