ISSN 2348-3156 (Print)
International Journal of Social Science and Humanities Research ISSN 2348-3164 (online)
Vol. 12, Issue 3, pp: (166-176), Month: July - September 2024, Available at: www.researchpublish.com

Training and Artificial Intelligence

Manal Al-otaibi

Puplic Authority for Applied Education and Training
Higher Institute of Administrative Services
English Department

DOI: https://doi.org/10.5281/zenodo.13268751

Published Date: 08-August-2024

Abstract: **Artificial intelligence is a branch of science that is growing at a fast rate to make computers behave like humans. Training and AI is one of the tech advancements that cover a wide range of areas like neural networks, natural language processing, gaming, robotics, and automation. Today, neural networks, computing, and automation are some of the hottest areas in AI that are successfully implemented in areas like natural language processing and voice recognition. This research paper explores the intersection of training and artificial intelligence (AI) and its implications for various industries. It examines different machine learning techniques like supervised, semi-supervised, and unsupervised learning, and reinforcement learning and their impact on the effectiveness and efficiency of AI algorithms. Also, the paper explores the deep learning concepts that are used in machine learning methods and presents an overview of machine learning algorithms and how they are applied in the implementation of AI systems.**

Keywords: **Machine Learning, Artificial Intelligence, Supervised Learning, AI Training, Deep Learning, Data Algorithms, Deep Learning.**

1. INTRODUCTION

We are in a digital era where nearly everything revolves around data, whether in the banking system, computing, blockchain, financial analysis, or agriculture. The IT world is surrounded by a wealth of all kinds of data from social media data, Internet of Things data, cybersecurity data, business data, health data, and smart city data. According to Sarker (2020), each set of data can either be structured, unstructured, or semi-structured, and it needs to be extracted, analyzed, and processed to be useful in real-world applications.

Artificial intelligence has emerged as one of the transformative technologies in recent years, revolutionizing industries by automating processes and enhancing decision-making capabilities (Lu, 2019). It refers to a machine's ability to mimic human intelligence and perform tasks that require human understanding like decision-making, problem-solving, learning, and natural language learning. The field incorporates AI technologies such as computer vision, robotics, natural language processing (NLP), and machine learning. The success of each AI model relies heavily on the training process. Training refers to teaching or guiding an AI system to perform specific tasks or learn patterns from data (Liu et.al, 2023). An AI model is exposed to a volume of labeled or unlabeled data and trained using algorithms to perform human-like tasks. In machine learning, algorithms are trained using raw data to learn and analyze its patterns and make decisions or predictions based on that data. The AI model learns through trial-and-error interactions with an environment.

Training AI models rely heavily on datasets to identify patterns that cannot be detected with basic analysis tools (Sarker, 2021b). This enables the algorithms to study the data and make predictions based on the results from the data. Deep learning is a subset of machine learning that focuses on neural networks to process complex data like speech and images and make intelligent decisions. On the other hand, computer vision is the ability of computers to acquire, analyze, and understand visual data like videos, images, and graphic information. Natural language processing combines techniques from machine learning, deep learning, and machine learning to analyze, process, interpret, and generate human language in a meaningful way (Le Glaz et al., 2021). NLP uses computational linguistics and supervised learning algorithms like maximum entropy, Bayesian networks, and support vector machines. According to research by Bharadiya (2023), NLP is heavily applied in tasks such as speech recognition, sentiment analysis, optical character recognition, and speech tagging.

ISSN 2348-3156 (Print)
International Journal of Social Science and Humanities Research ISSN 2348-3164 (online)
Vol. 12, Issue 3, pp: (160-165), Month: July - September 2024, Available at: www.researchpublish.com

Artificial intelligence is here to transform nearly every aspect of technology, paving the way for people to discover new ways of absorbing knowledge and performing tasks (Lu, 2019). It has influenced nearly every aspect of human life from gaming to coding, retail, and interactions. For instance, in social media, AI has been trained to understand conversations and go through users' clicks, interests, preferences, internet profiles, buying habits, age, and regions. Data collected is used by marketers to run targeted marketing campaigns to specific audiences without much human intervention (Parra, 2024). In artificial intelligence, training impacts the performance, accuracy, and generalization capabilities of AI systems. Well-trained models are more likely to provide accurate predictions, recognize patterns, and exhibit robust behavior in real-world scenarios. During the training process, AI models are exposed to massive amounts of data to identify complex patterns that may not be apparent to humans. As more information becomes available, AI systems get the flexibility to learn in a dynamic environment and improve their performance (Maity, 2019). Using diverse datasets enables the developers and trainers to mitigate biases that might be present in AI models.

2. STATEMENT OF THE PROBLEM

The integration of artificial intelligence into various industries like healthcare and manufacturing has led to a growing demand for effective training methodologies to ensure optimal performance and reliability of AI systems (Pruneski et al., 2022). However, the rapid advancements in AI tech present challenges and unsolved issues related to the training of AI models. This research aims at unmasking the quality and relevance of training data and the efficiency of training techniques and computational resources. The paper aims to answer questions like:

1. What are the training techniques in machine learning and deep learning?
2. What are the current limitations and challenges in training artificial intelligence models?
3. What are the potential implications and benefits of advanced AI training methods for different industries?
4. How can ethical concerns in AI like bias and fairness be mitigated?

3. LITERATURE REVIEW

As artificial intelligence keeps evolving, users should be aware that successful deployment relies on appropriate training methodologies. This literature review provides an overview of existing research and key insights into the training of AI models and techniques like deep learning and machine learning (Jiang et al., 2017). Also, it examines the studies to highlight the strengths of the methods, their limitations, and potential future considerations. Using the systematic literature review method, research on training and AI is limited to business strategy, supply chain, fake reporting, human resources, and management outcomes (Votto et al., 2021). However, there is limited research on machine learning algorithms and their real-world applications. Most of the research data is shallow and does not fully explain the current and potential future directions of AI. Previous studies have not provided in-depth information on the challenges and the adoption of training techniques in AI models.

Recent research explores the innovations in artificial intelligence, how they are adopted, and their execution in fields like education, communication, healthcare, manufacturing, research & development (R&D), and supply chain. From research by Aldoseri et. al. (2023), AI uses prominent paradigms within machine learning like supervised learning, unsupervised learning, and reinforcement learning to train AI models. Studies show by Sarker et. al. (2020) show that supervised learning involves training models on labeled data, providing a basis for tasks like regression and classification. On the other hand, unsupervised learning focuses on uncovering patterns and structures in labeled data. Reinforcement learning involves training agents to make sequential decisions through trial and error and is commonly applied in gaming and robotics.

Looking at the success of artificial intelligence in different applications, we can only acknowledge its importance on IT systems and the effectiveness of the adopted training methods (Lu, 2019). This literature review provides an overview of current research on training methods, focusing on machine learning, deep learning, and training techniques and tools. The study found that AI is widely applied in nearly every sector including in education and workplaces.

4. RESEARCH GAP

From the literature review above, it is clear that training plays a key role in artificial intelligence, especially in machine learning and deep learning. Scholars have done extensive research in this aspect although only a small number have taken the following paths.

- A limited number have discussed the application of AI to test emerging development and training techniques that can help advance AI research, practice, strategy, and education and increase its accuracy in coordination and human-like intelligence (Pruneski et al., 2022).

- Few studies discuss the scalability and efficiency of training models and AI architectures. There is little research on large-scale models that require sophisticated computational resources to deploy in resource-constrained environments.

- Generalization and transfer learning remain uncovered and the ability to generalize models across domains remains a critical challenge. Few scholars have covered the issues of current approaches to transfer learning when models are exposed to complex datasets or tasks. Future studies should explore novel transfer learning paradigms to enable models to generalize more effectively.

- Despite extensive research in adversarial robustness, existing defense mechanisms demonstrate limited efficacy or come with trade-offs in model performance. Scholars and R&D departments need to address this gap and expound more on ways to develop robust training techniques that improve model resilience against adversarial manipulation.

Types of Real-World Data and Machine Learning Techniques

The availability of data and the effectiveness of machine learning techniques used for training is central to the success of AI systems (Liu et. al., 2023). Real-world data is characterized by its diversity and complexity providing opportunities and challenges in training models. Machine learning and deep learning techniques offer powerful tools for extracting knowledge and patterns from data.

Types of Real-World Data

Data is essentially information, facts, images, videos, or statistics that are collected and stored for analysis and reference. In the context of AI, it is used by machine learning algorithms to train models to recognize patterns and perform tasks accurately. Raw data is used in combination with validation data to fine-tune the model's parameters during training to prevent overfitting (Lee & Cho, 2021). This happens when models perform well on training data but poorly when introduced to new data. In applications like deep learning, data is used to extract features that are relevant to the task at hand. These can be anything from pixel values in an image to word frequencies in text. The quality and relevance of the features determine a model's ability to learn and make accurate predictions fairly without bias (Praveen & Chandra, 2020). Data in artificial intelligence can be categorized into structured, semi-structured, and unstructured data.

Structured data has a well-defined structure and is well organized in a way that is easily accessible by a computer program. In well-defined schemes like relational databases and spreadsheets, structured data is stored in tabular format. It mostly contains numerical and categorical attributes that facilitate analysis and modeling using machine learning algorithms (Hopkins et al., 2022). Some case examples of structured data are stock information, credit card numbers, addresses, and names.

Semi-structured data lacks a strict schema but exhibits some level of organization but it's not stored in relational databases. It takes the form of HTML, JSON, XML, NoSQL databases, or key-value pairs. According to Sarker (2021), it is prevalent in web content, configuration files, and log files. While it's less organized, it offers scalability and flexibility, making it suitable for capturing heterogeneous information. However, it's more complex to process and analyze, especially when there are massive datasets.

Unstructured data lacks a predefined structure or format, making it more difficult to capture, process, analyze, and use in training AI models (Ravi et al., 2023). Mostly, it's made up of text and multimedia material like PDF files, word processing documents, emails, sensor data, video and audio files, presentations, web copy, and blog entries. Extracting meaningful information requires advanced natural language processing, audio processing techniques, and computer vision (Hopkins et al., 2022). Despite its inherent complexity, unstructured data contains valuable insights that can enrich AI applications in areas like speech recognition, image recognition, and sentiment analysis.

Datasets serve different purposes in machine learning, data science, training, and artificial intelligence. For instance, smartphone datasets serve in mobile app usage logs and call logs while cybersecurity datasets are used in Bot-IoT or incident analysis and response.

ISSN 2348-3156 (Print)
International Journal of Social Science and Humanities Research ISSN 2348-3164 (online)
Vol. 12, Issue 3, pp: (160-165), Month: July - September 2024, Available at: www.researchpublish.com

Types of Machine Learning Techniques

Machine learning algorithms are placed into four main categories which are supervised learning, semi-supervised learning, unsupervised learning, and reinforcement learning. Each technique provides powerful tools for extracting knowledge and patterns from data. They incorporate data processing, model evaluation, and feature engineering to boost performance and reliability in AI models.

Supervised learning involves training a model on labeled data, where each input is linked with a corresponding output. According to Sarker (2021), supervised learning is a task-driven approach whereby training is carried out when specific goals are achieved. It includes tasks like classification and regression. In classification, the model learns to predict discrete class labels while in regression, it predicts continuous numerical values. It's a strategy that uses algorithms like neural networks, support vector machines, and neural networks. Besides, it incorporates methods like random forests and gradient boosting. Mostly, supervised learning is adopted in AI applications such as predictive analytics, image classification, and spam detection (Hoover et al., 2023). Research suggests that supervised learning is an effective method when large amounts of labeled data are available. Another research argues it's a difficult method when obtaining labeled data is time-consuming.

Unlike supervised learning, *unsupervised learning* involves training models without labeled data. Instead, it identifies clusters or patterns within the input data to identify and study inherent structures and relationships. It heavily relies on clustering techniques like k-means clustering and dimensionality reduction methods like principal component analysis. Finding hidden patterns and detecting anomalies is easier when using this technique although it may lack interpretability due to the absence of explicit labels (Wittek, 2014). Clustering algorithms are used to group similar data points together while dimensionality reduction techniques aim to reduce the complexity of the data by capturing its essential features. Unsupervised learning uses other algorithms like hierarchical clustering, t-distributed stochastic neighbor embedding (t-SNE), and principal component analysis (Naeem et al., 2023). This technique is applied in training and AI in exploratory data analysis, anomaly detection, and customer segmentation.

Semi-supervised learning is a hybrid version of supervised and unsupervised techniques that work on both labeled and unlabeled data. In real-world applications, unlabeled is numerous while labeled data is limited making this method an excellent one in training AI applications (Engelen & Hoos, 2020). It aims at providing a better outcome for prediction that may not achieved when the learning is tied to one type of data. Semi-supervised learning is heavily applied in fraud detection, text classification, labeling data, and machine translation as used in Google Translate.

Reinforcement learning focuses on training AI models through trial-and-error interactions with the environment. Feedback is delivered in the form of rewards or penalties based on its action, guiding the model to learn optimal strategies. Although it has proven effective in robotics and game-playing agents, Dulac-Arnold et al. (2021) suggest that there are challenges in defining suitable reward structures and dealing with high-dimensional state-action spaces. Reinforcement learning heavily relies on algorithms like deep Q-networks (DQN), Q-learning, actor-critic methods, and policy gradients (AlMahamid & Grolinger, 2022). This enables it to offer promise in training AI systems to adapt and optimize their behavior in dynamic environments.

Training methods also call for data pre-processing and feature engineering. This involves cleaning, transforming, and preparing the data for modeling. Outlier detection, normalization, and missing value imputation take place in this step. Feature engineering covers selecting, creating, and transforming features to improve the performance of machine learning models (Sarker, 2021). Proper future engineering uses feature scaling, one-hot encoding, and dimensional reduction techniques for feature representation and optimal generalization. Machine learning models are evaluated to determine their reliability in real-world scenarios. Cross-validation is then done using stratified cross-validation or k-fold cross-validation to estimate the generalization performance of the model on unseen data (Kee et al., 2023). Hyperparameter tuning and model selection are executed to optimize the performance and robustness of the model.

Machine Learning Tasks and Algorithms

Machine learning has revolutionized strategies in training AI models, processing and analyzing data, and enabling intelligent systems to learn from experience (Lu, 2019). Classification, regression, cluster analysis, and transfer learning stand out as the building blocks to extracting knowledge and making predictions from data. In phase one of model training, historical data goes through machine learning algorithms and the results then get into the predictive mode. Here, data is collected and prepared for use in AI training. Natural processing methods require diverse datasets which can be collected through

ISSN 2348-3156 (Print)
International Journal of Social Science and Humanities Research ISSN 2348-3164 (online)
Vol. 12, Issue 3, pp: (160-165), Month: July - September 2024, Available at: www.researchpublish.com

crowdsourcing, automated collection, or in-house data collection (Sarker, 2021). The collected data is then processed and modeled to clean it up and maintain the relevance of the dataset. Modeling the data prepares it for training machine learning models and makes it easier to understand relationships, constraints, and relevant variables in the data (Pruneski et al., 2022). The collected data needs to be annotated and labeled to convert it into machine-readable format. Next, you need to determine and select the right model that will be used in the training step depending on the type of datasets available and the problem at hand. This may be models like decision trees, support vector machines, neural networks, random forests, or deep learning among others. Phase two is model testing where new data is taken into the predictive mode to produce predictions or outcomes. There will be a likelihood of overfitting if the model performs well on training data and poorly when introduced to new test data (De Silva & Alahakoon, 2022). If this happens, it means the model has mastered the training data instead of the patterns in the data.

Classification Analysis

Classification is a supervised learning method where the goal is to predict discrete class labels for input data instances (Sarker, 2021). It's mainly applied in spam detection, image classification, and sentiment analysis. It maps out a function (f) mathematically from input variables (x) and output variables (y) as labels, categories, or targets. The choice of the algorithm used in classification analysis depends on class distribution, interpretability requirements, and data complexity (Strecht et al., 2015). Class predictions can be done either on structured or unstructured data. For instance, spam detection in emails can be viewed as a classification problem whereby it's labeled as either 'spam' or 'not spam'. Evaluation metrics are done to assess the performance of classification models and guide model selection (Ravi et al., 2023). In artificial intelligence, classification can be binary, having two labels as "yes and no" or "true and false", multiclass where tasks have more than two labels, or multi-label where there are several labels or classes.

Regression Analysis

Regression analysis is a supervised learning task that includes several methods of machine learning to predict continuous numerical values based on input features (Zurada et al., 2011). Unlike classification which predicts distinct labels, regression enables the prediction of a continuous quantity. It's used in financial forecasting, data science, and healthcare. This method uses algorithms like polynomial, ridge, and linear regression, decision trees, SVR, and neural networks. Evaluation metrics like R-squared, mean absolute error, and mean squared error are used to quantify the predictive performance of regression models.

Cluster Analysis

Clustering is an unsupervised learning task aimed at grouping similar data points based on their intrinsic characteristics. The clustering algorithms partition the data into clusters such that data points within the same cluster are more similar to each other than to those in other clusters (Kitahara & Holm, 2018). This training method uses algorithms like hierarchical clustering, DBSCAN, k-means clustering, and Gaussian mixture models (GMM). The quality of the results is determined using evaluation metrics like the Davies-Bouldin index and silhouette score which also guide algorithm selection.

Transfer Learning

This technique addresses the challenge of leveraging knowledge from one task or domain to improve learning performance in another task. Transferring learned representations or models allows for the effective usage of limited labeled data and speeds up model training (De Silva & Alahakoon, 2022). Transfer learning trains the mode using techniques like feature extraction, fine-tuning pre-trained models, and domain adaptations. Pre-trained models like Bidirectional Encoder Representations from Transformers (BERT) and ResNet have been successfully applied across various tasks and domains. Using transferable knowledge or pre-trained models eliminates the need for extensive training data and computation resources (Kitahara & Holm, 2018). Evaluation of transfer learning models includes assessing their performance on target tasks or domains and analyzing the transferability of learned representations.

The Position of Deep Learning in Training and Artificial Intelligence

Deep learning has emerged as a transformative force in training AI models and enhancing the machines' capabilities to learn from data (Soori et al., 2023). It is a subset of machine learning inspired by the structure and function of the human brain. Over the years, it has demonstrated unparalleled performance in tasks like speech recognition, natural language processing, and image recognition. Building appropriate deep-learning models can be complex due to the nature of data and variations in real-world problems (Pruneski et. al., 2022). Inspired by the structure and function of the human brain, deep learning encompasses neural networks with multiple layers of interconnected nodes. The fundamental architectures of DL are recurrent neural networks (RNNs), convolutional neural networks (CNNs), and deep belief networks (DBNs), with each tailored to specific types of data and tasks.

The versatility of deep learning has made it an excellent application across domains like healthcare, finance, telecommunications, entertainment, and automotive. For instance, Tesla equips their cars with sophisticated lane-keeping features and AI-powered autosteers to enable them to navigate through curves and stay within the lanes, even on roads with sharp corners.

Machine learning algorithms are used to process and analyze data and train Tesla's AI systems. According to Kumari & Bhat (2021), Tesla heavily uses AI in their vehicles, particularly for its full self-driving (FSD) capabilities and autopilot. The systems rely on machine learning algorithms and neural networks to process large amounts of data from sensors, cameras, radar, and ultrasonic sensors (Soori et al., 2023. This enables the vehicle to perceive its surroundings and make driving decisions. In Tesla's case, the automaker collects data from its fleet of vehicles through over-the-air updates, which allows it to continually improve the AI algorithms deployed to train the models. The models are fed with large datasets of labeled sensor data like images of pedestrians, vehicles, and roads, together with corresponding actions taken by human drivers in those situations. The AI learns to identify patterns and make decisions based on the data, improving its performance through iterations of training and testing. Tesla employs a special technique called "fleet training," where data collected from the entire fleet of Tesla cars is aggregated and used to improve the performance of the models (Kumari & Bhat, 2021). This is just an example of how machine learning and deep learning algorithms are applied to real-world problems. When it comes to healthcare, the algorithms are employed for personalized treatment planning, drug discovery, disease diagnosis, and medical image analysis (Jiang et al., 2017). In finance, deep learning facilitates customer relationship management, algorithmic trading, and fraud detection. Also, they are prevalent in natural language processing tasks like speech recognition and language translation like in Speechelo and Google Translate. In communication and social media, deep learning is used to process large volumes of data from different sources like websites, social media platforms, and apps to identify trends and patterns in user data, interests, preferences, and behaviors.

Deep Learning and Training

At its core, deep learning involves the training of neural networks with multiple layers of interconnected nodes, known as neurons. These layers enable the network to automatically learn hierarchical representations of data to facilitate the extraction of complex patterns and features (Bharadiya, 2023). The process of training deep learning models involves forward propagation data through the network followed by backpropagation of errors to adjust the network parameters iteratively.

Today, machine learning, artificial intelligence, and deep learning are used interchangeably in model training, testing, and execution. Machine learning models learn from experience or data while AI incorporates human intelligence and behaviors into the systems or machines. In deep learning, data computation and model training are done through multi-layer processing and neural networks. Due to its capabilities, DL is heavily used in data science to find insights and meaning from data (Sarker, 2021). The sophisticated tasks that can be performed by this technique show how far technology has advanced and its power in solving real-world solutions.

Different forms of data in deep learning

Deep learning's ability to learn from complex patterns from different data sources shows how far it has evolved in training deep learning models. The representation of data is important in model training and testing. In DL, data can be in various forms like sequential data, image or 2D data, or tabular data.

Sequential data represents information that is structured or ordered in a sequence such as text or time series data (Sarker, 2021). It is processed using techniques like RNNs, long short-term memory (LSTM) networks, and gated recurrent units (GRUs) due to their ability to capture temporal dependencies. When building the model, the algorithm accounts for the sequential nature of input data whether it's video clips or text streams.

*Image or 2D da*ta consists of visual information or digital images represented in the form of pixels arranged in a grid. CNNs are the cornerstone of deep learning for image-related tasks due to their ability to extract hierarchical representations and spatial features. The fundamental parameters and characteristics of an image are bit depth, pixels, matrix, and voxels. The learning on image data is applied in style transfer, image classification, segmentation, and object detection (Afzal et al., 2023). However, the processing of image data is prone to overfitting, occlusion, and challenges in handling large data volumes.

Tabular data is structured in rows and columns, as found in databases, CSV files, and spreadsheets. Previously, traditional machine learning algorithms like decision trees and random forests have been used for tabular data analysis. Today, deep learning models like gradient boosting machines and feedforward neural networks appear to be more effective in classification and regression (Ullah et al., 2022). In tabular data, each field (column) must have a name and data of a particular type. It's easier to use in deep learning models as data in rows and columns is organized based on features and properties.

Deep Networks for Supervised or Discriminative Learning

Unlike traditional machine learning algorithms, deep learning models automatically extract features at multiple levels of abstraction to create state-of-the-art tasks. Descriptive deep architectures are neural network models that are designed to provide descriptive power for regression and classification (Liu et al., 2011). Some of the main architectures in deep learning include MLP, CNN or ConvNet, and RNNs.

Convolutional Neural Networks (CNNs) have transformed the field of computer vision by enabling machines to understand and interpret visual data with remarkable accuracy (Indolia et al., 2018). Inspired by the visual cortex of the human brain, CNNs are designed to automatically learn hierarchical representations from image data. The architecture comprises of multiple layers like pooling, convolutional, and fully connected layers. Convolutional layers extract features from the input images by applying a series of learnable filters and capturing spatial patterns like shapes, textures, and edges (Sarker, 2021). Pooling layers downsample the feature maps to reduce computational complexity and improve translational variance. Fully connected layers then integrate the extracted features for classification or regression tasks. The training of CNNs involves feeding labeled data into the network and adjusting the parameters (weights and biases) using optimization algorithms like Adam and stochastic gradient descent (SGD). In the training phase, the network learns how to minimize a predefined loss function which measures the disparity between the predicted outputs and the ground truth labels (Yamashita et al., 2018). Backpropagation is used to compute the gradient of the loss function in relation to the network parameters, facilitating parameter updates through gradient descent.

Multi-layer Perceptrons (MLPs) are a type of feedforward artificial neural network comprising multiple layers of interconnected nodes or neurons (Isabona et al., 2022). Each neuron receives input signals, processes them through a series of weighted connections, and generates an output signal based on an activation function. This architecture contains an input layer, one or more hidden layers, and an output layer. The transformative power of MLPs stems from their ability to learn complex patterns and relationships within data. During training, the model adjusts its internal parameters to minimize the discrepancy between predicted outputs and truth labels. The output is determined by transfer functions like Sigmoid, Softmax, Tanh, and Rectified Linear Unit (ReLU). Like in CNNs, the training process uses backpropagation algorithms, a technique in supervised learning, and gradient descent to train the MLP models (Alsmadi et al., 2009). It applies optimization approaches like Adam, Limited Memory BFGS, and SGD. In computer vision, MLP is used in combination with CNNs for tasks such as semantic segmentation, object detection, and image classification. Besides, in natural language processing, LSTM networks and RNNs employ MLP architectures to process model temporal dependencies and sequential data (Le Glaz et al., 2021). Despite its effectiveness in training AI models, MLP is overly expensive as it requires fine-tuning of hyperparameters like iterations and neurons.

Recurrent Neural Networks (RNNs) and their variants have emerged as powerful tools for processing sequential data, allowing models to capture patterns and temporal dependencies (Hewamalage et al., 2021). Unlike feedforward neural networks, RNNs possess internal memory, enabling them to maintain information about past inputs. They are characterized by their ability to process sequences of inputs by maintaining hidden states that capture temporal dependencies. The architecture of an RNN contains recurrent connections that allow information to persist over time (Lipton et al., 2015). Training RNNs involves optimizing the model parameters to minimize a predefined loss function. It uses methodologies such as gradient descent and backpropagation algorithms. RNNs have variants like long short-term memory, gated recurrent

ISSN 2348-3156 (Print)
International Journal of Social Science and Humanities Research ISSN 2348-3164 (online)
Vol. 12, Issue 3, pp: (160-165), Month: July - September 2024, Available at: www.researchpublish.com

units, and bidirectional RNN/LSTM. LTSM is used to solve the vanishing gradient problem. It's made of the input gate which determines the information getting to the cell state, the forget gate which determines useful information and what is no longer useful, and the output gate which controls the outputs (Sarker, 2021). Bidirectional RNN/LSTM connects hidden layers running in different directions into a single entity. Gated recurrent unit uses gated methods to control the flow of information between cells in the network. LTSM has three gates which are input, forget, and output, while GRU has two namely reset and update gates (Kumar et al., 2018). In the training phase, RNNs also use force teacher training techniques in sequence prediction tasks. The model is fed with the ground truth output from the previous time step during training. Scheduled sampling gradually transitions from using ground truth tokens to using model predictions. Attention mechanisms are used to enable RNNs to focus on relevant parts of the input sequence when making predictions. They are adopted in sequence-to-sequence models for machine translation and text summarization.

Deep Networks for Generative or Unsupervised Learning

Generative modeling or unsupervised learning are fundamental tasks in machine learning that aim to capture the underlying distribution of data and extract useful information without supervision(Lu, 2019). Deep generative models like GAN, autoregressive models, and autoencoders have emerged as powerful frameworks for training generative models.

Generative Adversarial Networks (GANs) represent a key breakthrough in model training making it easier for AI systems to create new data instances that resemble real-world samples. The network architecture learns patterns and regularities in input data and outputs or generates new examples from the original data (Sarker, 2021). GANs use a generator and discriminator during the training phase. The generator learns ways to produce synthetic data samples from the input data while the discriminator distinguishes between real and fake data (Aggarwal et al., 2021). Through iterative training, the generator produces realistic samples that make it possible to generate highly realistic instances (Maity, 2019). The training process of GANs involves a minimax game between the generator and the discriminator. Over time, the gradients of the discriminator's loss are used to update its parameters, while the gradients of the generator's loss are used to update the generator's parameters. This adversarial training process continues until convergence, resulting in a generator that produces indistinguishable samples from the real data distribution.

Autoencoders represent a class of unsupervised learning algorithms in deep learning that are designed to learn efficient representations of input data by compressing and reconstructing it. Generally, autoencoders are designed to work with high-dimensional data. An encoder is made up of an encoder, code, and decoder. The encoder compresses the input data into a latent representation or code while the decoder reconstructs the original input data from this code. The latent space serves as a compressed and informative representation of the input data, facilitating tasks like anomaly detection, denoising, and generation (Zhai et al., 2018). In the training phase, reconstruction loss needs to be reduced, and it's measured by the variation between the input data and the reconstructed output. This loss encourages the autoencoder to learn a compact representation of the input data that captures key features while minimizing reconstruction error. Training autoencoder models can be done using optimization algorithms like Adam and SGD.

Self-Organizing Maps (SOMs) or Kohonen maps are unsupervised neural network models that are capable of learning and representing complex high-dimensional data in a low-dimensional space (Riese et al., 2020). SOMs consist of a grid of neurons arranged in a low-dimensional lattice, like a two-dimensional grid. Each neuron is associated with a weight vector that represents a prototype or cluster center in the input space. During training, the neurons compete to respond to input patterns, and the winning neuron and its neighboring neurons are adjusted to better represent the input data distribution. Initially, the weights of the neurons are randomly initialized. As input samples are represented, the neuron with the weight vector closest to the input pattern is identified as the winner. The winning neuron and its neighbors in the lattice are then updated to move closer to the input pattern. They follow a neighborhood function that decreases with time. SOMs can learn to extract salient features from input data, providing a compact representation that captures critical characteristics of the dataset (Bock, 2000). Feature maps learned by SOMs can be used as input for downstream tasks like classification and regression.

5. CONCLUSION

The training of artificial intelligence models represents a cornerstone in the advancement of intelligent systems across different domains. From the present studies, we can see the utilization of various machine learning and deep learning techniques in model training and AI. This study provides a comprehensive foundation on AI architectures and deep learning and how different techniques are applied in training.

Machine learning and deep learning provide pivotal contributions to training. This study showcases their ability to leverage large volumes of data to extract meaningful patterns and representations to make accurate predictions and generate new data instances. The iterative process of training involves adjusting the parameters of models based on feedback signals to minimize prediction errors and maximize outcomes. The study identified CNNs and RNNs as effective architectures in deep learning to train AI models. The field of training is characterized by continuous innovation and exploration of novel techniques and algorithms for supervised, unsupervised, and reinforcement learning. Researchers are pushing the boundaries on what this field can achieve, whether in developing efficient optimization algorithms, devising new training strategies, or designing architectures. Present studies need to come up with more effective ways to solve challenges like vanishing gradients, data scarcity, and overfitting. While present studies have established a solid foundation for deep learning systems, machine learning, and artificial intelligence, there is still room for research on deep networks for supervised and unsupervised learning, data preparation to maintain data quality, hyper-parameter values for model training, and computational efficiency.

REFERENCES

[1] Afzal, S., Ghani, S., Hittawe, M. M., Rashid, S. F., Knio, O. M., Hadwiger, M., & Hoteit, I. (2023). Visualization and visual analytics approaches for image and video datasets: A survey. ACM Transactions on Interactive Intelligent Systems, 13(1), 1–41. https://doi.org/10.1145/3576935

[2] Aggarwal, A., Mittal, M., & Battineni, G. (2021). Generative Adversarial Network: An overview of theory and applications. International Journal of Information Management Data Insights, 1(1), 100004. https://doi.org/10.1016/j.jjimei.2020.100004

[3] Aldoseri, A., Al-Khalifa, K. N., & Hamouda, A. M. (2023). Re-thinking data strategy and integration for Artificial Intelligence: Concepts, opportunities, and challenges. Applied Sciences, 13(12), 7082. https://doi.org/10.3390/app13127082

[4] AlMahamid, F., & Grolinger, K. (2022, September 29). Reinforcement learning algorithms: An overview and classification. arXiv.org.

[5] Bock, H.-H. (2000). Regression-type models for Kohonen's self-organizing networks. Studies in Classification, Data Analysis, and Knowledge Organization, 18–31.

[6] Bharadiya, J. . (2023). A Comprehensive Survey of Deep Learning Techniques Natural Language Processing. European Journal of Technology, 7(1), 58 – 66.

[7] Chai, S. S., Cheah, W. L., Goh, K. L., Chang, Y. H. R., Sim, K. Y., & Chin, K. O. (2021, December 7). A multilayer perceptron neural network model to classify hypertension in adolescents using anthropometric measurements: A cross-sectional study in Sarawak, Malaysia. Computational and Mathematical Methods in Medicine. https://www.hindawi.com/journals/cmmm/2021/2794888/

[8] De Silva, D., & Alahakoon, D. (2022). An artificial intelligence life cycle: From conception to production. Patterns, 3(6), 100489. https://doi.org/10.1016/j.patter.2022.100489

[9] Dulac-Arnold, G., Levine, N., Mankowitz, D. J., Li, J., Paduraru, C., Gowal, S., & Hester, T. (2021). Challenges of real-world reinforcement learning: Definitions, benchmarks and analysis. Machine Learning, 110(9), 2419–2468.

[10] Hewamalage, H., Bergmeir, C., & Bandara, K. (2021). Recurrent neural networks for time series forecasting: Current status and future directions. International Journal of Forecasting, 37(1), 388–427. https://doi.org/10.1016/j.ijforecast.2020.06.008

[11] Hoover, B., Zaengle, D., Mark-Moser, M., Wingo, P., Suhag, A., & Rose, K. (2023). Enhancing knowledge discovery from unstructured data using a deep learning approach to support subsurface modeling predictions. Frontiers in Big Data, 6. https://doi.org/10.3389/fdata.2023.1227189

[12] Hopkins, D., Rickwood, D. J., Hallford, D. J., & Watsford, C. (2022). Structured data vs. unstructured data in machine learning prediction models for suicidal behaviors: A systematic review and meta-analysis. Frontiers in Digital Health, 4. https://doi.org/10.3389/fdgth.2022.945006

[13] Indolia, S., Goswami, A. K., Mishra, S. P., & Asopa, P. (2018). Conceptual understanding of convolutional neural network- a deep learning approach. Procedia Computer Science, 132, 679–688. https://doi.org/10.1016/j.procs.2018.05.069

[14] Isabona, J., Imoize, A. L., Ojo, S., Karunwi, O., Kim, Y., Lee, C.-C., & Li, C.-T. (2022). Development of a multilayer perceptron neural network for optimal predictive modeling in urban microcellular radio environments. Applied Sciences, 12(11), 5713. https://doi.org/10.3390/app12115713

[15] Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial Intelligence in healthcare: Past, present and future. Stroke and Vascular Neurology, 2(4), 230–243. https://doi.org/10.1136/svn-2017-000101

[16] Kee, E., Chong, J. J., Choong, Z. J., & Lau, M. (2023). A comparative analysis of cross-validation techniques for a smart and lean pick-and-place solution with Deep Learning. Electronics, 12(11), 2371. https://doi.org/10.3390/electronics12112371

[17] Kitahara, A. R., & Holm, E. A. (2018). Microstructure cluster analysis with transfer learning and unsupervised learning. Integrating Materials and Manufacturing Innovation, 7(3), 148–156. https://doi.org/10.1007/s40192-018-0116-9

[18] Kumar, J., Goomer, R., & Singh, A. K. (2018). Long short term memory recurrent neural network (LSTM-RNN) based workload forecasting model for cloud datacenters. Procedia Computer Science, 125, 676–682. https://doi.org/10.1016/j.procs.2017.12.087

[19] Kumari, D., & Bhat, S. (2021). Application of artificial intelligence in tesla- A case study. International Journal of Applied Engineering and Management Letters, 205–218. https://doi.org/10.47992/ijaeml.2581.7000.0113

[20] Lee, Y., & Cho, J. (2021). Development of an artificial intelligence education model of classification techniques for non-computer majors. JOIV : International Journal on Informatics Visualization, 5(2), 113–119. https://doi.org/10.30630/joiv.5.2.552

[21] Le Glaz, A., Haralambous, Y., Kim-Dufor, D.-H., Lenca, P., Billot, R., Ryan, T. C., Marsh, J., DeVylder, J., Walter, M., Berrouiguet, S., & Lemey, C. (2021). Machine learning and natural language processing in mental health: Systematic review. Journal of Medical Internet Research, 23(5). https://doi.org/10.2196/15708

[22] Lipton, Z., Berkowitz, J., & Elkan, C. (2015). A Critical Review of Recurrent Neural Networks for Sequence Learning. Cornel University.

[23] Liu, B., Cai, G., Qian, J., Song, T., & Zhang, Q. (2023). Machine learning model training and practice: A study on constructing a novel drug detection system. International Journal of Computer Science and Information Technology, 1(1), 139–146. https://doi.org/10.62051/ijcsit.v1n1.19

[24] Liu, Y., Zhou, S., & Chen, Q. (2011). Discriminative deep belief networks for Visual Data Classification. Pattern Recognition, 44(10–11), 2287–2296. https://doi.org/10.1016/j.patcog.2010.12.012

[25] Lu, Y. (2019). Artificial intelligence: a survey on evolution, models, applications and future trends. Journal of Management Analytics, 6(1), 1–29. https://doi.org/10.1080/23270012.2019.1570365

[26] Maity, S. (2019). Identifying opportunities for artificial intelligence in the evolution of training and development practices. Journal of Management Development, 38(8), 651–663. https://doi.org/10.1108/jmd-03-2019-0069

[27] Naeem, S., Ali, A., Anam, S., & Ahmed, M. M. (2023). An unsupervised machine learning algorithms: Comprehensive review. International Journal of Computing and Digital Systems, 13(1), 911–921.

[28] Parra, J. L., & Chatterjee, S. (2024). Social Media and Artificial Intelligence: Critical Conversations and where do we go from here? Education Sciences, 14(1), 68. https://doi.org/10.3390/educsci14010068

[29] Praveen, S., & Chandra, U. (2021). (PDF) influence of structured, semi- structured, unstructured data on various data models. *Research Gate*.

[30] Pruneski, J. A., Williams, R. J., Nwachukwu, B. U., Ramkumar, P. N., Kiapour, A. M., Martin, R. K., Karlsson, J., & Pareek, A. (2022a). The development and deployment of Machine Learning Models. Knee Surgery, Sports Traumatology, Arthroscopy, 30(12), 3917–3923. https://doi.org/10.1007/s00167-022-07155-4

[31] Ravi, O, Rajnikant, S., Bhavans, D., Dipti, H., & Domadiya. (2023). Role of AI for gaining essential insight from unstructured data.

[32] Riese, F. M., Keller, S., & Hinz, S. (2019). Supervised and semi-supervised self-organizing maps for regression and classification focusing on hyperspectral data. Remote Sensing, 12(1), 7. https://doi.org/10.3390/rs12010007

[33] Sarker IH, Hoque MM, MdK Uddin, Tawfeeq A. Mobile data science and intelligent apps: concepts, ai-based modeling and research directions. Mob Netw Appl, pages 1–19, 2020.

[34] Sarker, I. H. (2021). Deep learning: A comprehensive overview on techniques, taxonomy, applications and Research Directions. SN Computer Science, 2(6). https://doi.org/10.1007/s42979-021-00815-1

[35] Sarker, I. H. (2021b). Machine learning: Algorithms, real-world applications and Research Directions. SN Computer Science, 2(3). https://doi.org/10.1007/s42979-021-00592-x

[36] Silva, M. P., Rupasingha, R. A., & Kumara, B. T. (2022). A comparative study of predicting students' academic performance using classification algorithms. 2022 2nd International Conference on Advanced Research in Computing (ICARC). https://doi.org/10.1109/icarc54489.2022.9753729

[37] Ullah, I., Rios, A., Gala, V., & Mckeever, S. (2021). Explaining deep learning models for tabular data using layer-wise relevance propagation. Applied Sciences, 12(1), 136.

[38] van Engelen, J. E., & Hoos, H. H. (2019). A survey on semi-supervised learning. Machine Learning, 109(2), 373–440. https://doi.org/10.1007/s10994-019-05855-6

[39] Votto, A. M., Valecha, R., Najafirad, P. and Rao, H. R. (2021), "Artificial Intelligence in Tactical Human Resource Management: A Systematic Literature Review", International Journal of Information Management Data Insights, Vol. 1 No. 2, pp. 100047.

[40] Wittek, P. (2014). Unsupervised learning. Quantum Machine Learning, 57–62. https://doi.org/10.1016/b978-0-12-800953-6.00005-0

[41] Yamashita, R., Nishio, M., Do, R. K., & Togashi, K. (2018). Convolutional Neural Networks: An overview and application in Radiology. Insights into Imaging, 9(4), 611–629. https://doi.org/10.1007/s13244-018-0639-9

[42] Zhai, J., Zhang, S., Chen, J., & He, Q. (2018). Autoencoder and its various variants. 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC). https://doi.org/10.1109/smc.2018.00080

[43] Zurada, J., Levitan, A., & Guan, J. (2011). A comparison of regression and artificial intelligence methods in a mass appraisal context. Journal of Real Estate Research, 33(3), 349–388. https://doi.org/10.1080/10835547.2011.12091311