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# **Techniques and Applications for Deep Learning: A Review**

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#### ABSTRACT

Deep learning is a branch of machine learning that focuses on the development and refinement of complex neural networks for data analysis, prediction, and decision-making. Deep learning models use numerous layers of artificial neurons to automatically extract important features from raw data, making them superior at many tasks to typical machine learning models. Deep learning models' success in these fields has enhanced state-of-the-art performance and created new research and application prospects. Deep learning has been popular due to its capacity to tackle complicated issues in computer vision, natural language processing, speech recognition, and decision-making. In this study, we discuss deep learning techniques and applications, including recurrent neural networks, long short-term memory, convolutional neural networks, generative adversarial networks, and autoencoders. We also demonstrate deep learning's use in various fields. Deep learning has transformed artificial intelligence by enabling computers to learn from enormous datasets and accomplish complex tasks. As a result, scientists and engineers in fields as diverse as medicine, farming, manufacturing, and transportation have increased their focus on developing deep-learning methods and software. Current research trends and potential future paths in deep learning are also highlighted.

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## 1. Introduction

Artificial intelligence (AI) which is the process of making machines as intelligent as the human brain, is when a machine can carry out tasks that people typically associate with human minds, such as learning and problem-solving. Machine learning is a subset of AI and deep Learning is the subfield of machine learning that focuses on the creation and education of artificial neural networks. With the advent of deep learning techniques, it is now possible for computers to learn from large datasets and make highly accurate predictions or decisions [1] Convolutional neural networks (CNNs) are widely used in deep learning for image recognition and computer vision applications. CNNs are commonly used for tasks like object detection, image classification, and facial recognition because of their ability to recognize patterns and features within images. Recurrent neural networks (RNNs) are another useful method; they

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are frequently employed in natural languages processing tasks like language translation and text classification, RNNs are used for pattern recognition and are optimized for use with sequential data like text and speech. Many other deep learning architectures and frameworks are also widely used in academia and the business world. Autoencoders, generative adversarial networks(GANs), and reinforcement learning are some examples [2].

Computer vision, speech recognition, NLP, autonomous vehicles, healthcare, and a great many other fields can all benefit from deep learning. For instance, deep learning is used in speech recognition systems, medical imaging for the detection of tumors and other abnormalities, and self-driving cars for object and pedestrian recognition[3]. Researchers and practitioners use Python and other programming languages, frameworks like TensorFlow and PyTorch, and specialized hardware like GPUs to develop and apply deep learning techniques. Additionally, model selection, evaluation, and hyperparameter tuning are all part of deep learning's process. The healthcare, financial, and advertising sectors, medical image analysis, drug discovery, and patient diagnosis are just some of the healthcare applications of deep learning[4]. Fraud detection and risk assessment, customer segmentation, recommendation systems, and personalized advertising are just a few examples of how deep learning is being put to use in the world of marketing.

In this research, we have touched upon some of the fundamental concepts and applications of deep learning. As deep learning continues to advance and impact numerous fields, it is essential to stay up-to-date with the latest techniques and tools to effectively apply this technology to real-world problems [5]. Overall, deep learning has the potential to revolutionize many industries and create new opportunities for innovation and growth. As the field continues to evolve, it will see new techniques and applications that emerge. Deep learning techniques are briefly discussed in Section 2, deep learning frameworks are highlighted in Section 3, and deep learning applications are summarized in Section 4. Finally, Section 5 gives a conclusion of the study.

### 2. Methodology of deep learning techniques

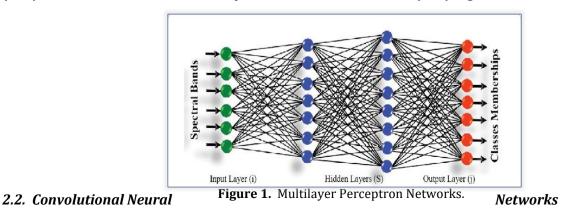
Deep learning networks are including several types:

- Multilayer Perceptron Networks (MLP) •
- Convolutional Neural Networks (CNNs)
- Recurrent Neural Networks (RNNs) •
- Long Short-Term Memory (LSTM) •
- Autoencoders (AE)
- Generative Adversarial Networks (GAN)

Parameters, applications, and input data all vary amongst these models, and unsupervised pre-training and supervised fine-tuning are the two main training strategies for modern deep learning systems [6].

### 2.1. Multilayer Perceptron Networks (MLP)

A multi-layer perceptron (MLP) is a type of artificial neural network that uses feed-forward. In supervised learning problems, we employ feedforward networks or multilayer perceptron networks. The architecture of an MLP consists of at least three layers of nodes: an input layer, one or more multiple hidden layers of computation nodes in the dataset's hidden layers to capture more intricate correlations, and an output layer and propagation for training[7]. Backpropagation is a supervised learning technique used to train the network. Each node, except the input nodes, is a neuron with a nonlinear activation function. The multilayer perceptron is the simplest type of deep neural network (MLP), which is also referred to as a "deep feedforward neural network" (DFN), Figure 1 illustrates an MLP [7].





A simple convolutional neural network (CNN) is described as a set of convolutional layers connected by pooling layers and non-linearity to transform one type of activation received at one end into a different type of activation received at the other end using a loss function. It is best to divide a picture into overlapping image tiles and submit them to a tiny neural network rather than feed the network an image as a grid of numbers. The network's very good feature extractor, which is even better than handcrafted features, however, requires more time to train and test as the number of nodes grows. ConvNet adjusts its weight to provide the appropriate output by backpropagation, as depicted in Figure 2 [8].

#### 2.2.1. CNN Architecture

- **Convolutional layer**: Filters or kernels for convolutional computation are used to create convolutional layers. These filters divide the entire image into three or five small grids and then convolve these small grids with kernels or filters to create a feature map. In CNN the convolution layer is the most crucial one because it takes up the majority of the network's time, extracts local spatial data, and performs the majority of the computationally intensive tasks[6].
- **Pooling layer:** This layer is added after the ReLU layer and before the convolutional layer, the pooling layer promotes translational invariance in networks, strengthens the output features' resistance to feature relocation in the image, and helps prevent overfitting[6].
- **Fully-connected layer:** This layer is in charge of carrying out the entire process by taking input from all feature extraction layers and doing a global analysis of the output from all preceding layers. It is fully connected to all activations of the previous layers[6].
- Activation functions: Activation processes help neural networks make decisions and learn intricate aspects from incoming images. When learning complicated patterns from raw input data, using the right activation function can speed up the training process [6].

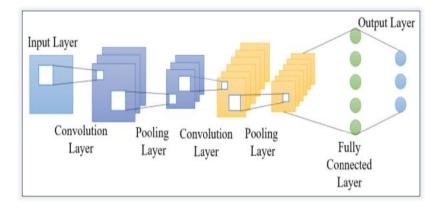


Figure 2. Convolutional Neural Networks architecture.

#### 2.2.2. Transfer Learning

Convolutional neural networks (CNN) were trained on a large and diverse dataset (ImageNet). Deep learning models develop model weight and bias while being trained with a big volume of data, then alternative network models are tested using these weights. Pre-trained models are used since learning a network from scratch can take weeks and requires more processing power when training massive models on massive datasets. Using weights that have already been trained to train the new network helps speed up learning [9]. The two most popular methods include using models that have undergone extensive pre-training and fine-tuning. These models can be applied directly or through transfer learning, and they can be modified as necessary the model can be pre-trained using publicly available datasets, and the feature extractor settings can be reused [10]. In recent years have seen considerable advancements in deep network architecture with numerous pre-trained models already present in libraries, Keras and TensorFlow. There are many pre-trained architectures available, such as VGG16, VGG1, GoogleNe, ResNet50, InceptionV3, MobileNet, and Xception. The convolutional network architecture used by the VGG and AlexNet networks is conventional[11]. MobileNet is an Xception architecture that has been simplified and is tailored for mobile apps.

EfficientNet, ResNet, Inception, Xception[12], and RegNet architectures, as a result of their adaptability, have become reference points for future studies on computer vision [11].

### 2.3. Recurrent Neural Networks

The original application of backpropagation was for training recurrent neural networks (RNNs). When the task at hand calls for sequential inputs, RNNs are often the preferred choice. For example, speech and language can process an input sequence element by element and store a state vector in their latent units, which contains implicit knowledge of the history of all elements in the sequence. It is possible to train RNNs with backpropagation, as shown in Figure 3 [13], by treating the outputs of the hidden units at different discrete time steps as though they were the outputs of different neurons in a deep multilayer network.

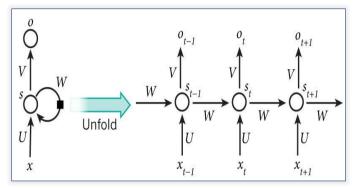


Figure 3. Recurrent Neural Networks architecture.

# 2.4. Long Short-Term Memory

An application of a recurrent neural network is the LSTM; in contrast to feed-forward network topologies, the LSTM can remember previous states and be taught for tasks requiring memory. Gradients can flow through LSTM without being altered, which overcomes a significant RNN constraint. Due to RNN's ability to retain information in both long-term and short-term memory, it is possible to utilize it to predict time series. As illustrated in Figure 4 [14], Signals pass through blocks of memory cell state in an LSTM, It is managed by input, forget, and output gates.

These gates regulate the cell's methods for storing, reading, and writing information. Long Term dependencies can be tracked using LSTM recurrent neural networks, as a result, sequential data and models that rely on context and previous states are well suited to these learning strategies. LSTM-blocked cells store important info from earlier states and the cell values needed to generate the LSTM block's output are determined by the input, forget, and output gates respectively [15].

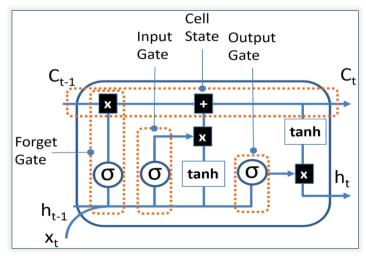


Figure 4. Long Short-Term Memory architecture.

#### 2.5. Autoencoders

Autoencoders are neural network (NN) algorithms that are used to efficiently code a dataset to reduce its dimensionality. One key advantage of the AE is that it can continuously extract useful features while propagating and filtering out useless information. Input is compressed and then decoded to reconstruct it; lower hidden layers are used for encoding, and higher hidden layers are used for decoding. Layers for decoding and error back-propagation are used for training[6]. To save on compute resources, autoencoders learn to decode compressed data by coding it in a supervised fashion and training just one layer for each operation. The autoencoder procedure uses a network to encrypt the data in the hidden layer if the input and output layers are more dimensional, this is known as feature compression, Figure 5 [15] shows a deep autoencoder representation.

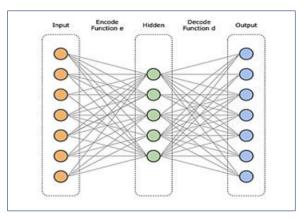


Figure 5. Autoencoders architecture.

### 2.6. Generative Adversarial Network

Through unsupervised learning, the generative model technique GAN may learn to replicate a certain information distribution. These algorithms efficiently strip the data down to its core characteristics or produce brand-new data points with unique characteristics. In several pictures generating tasks, such as text-to-image synthesis, super-resolution, and image-to-image translation, it has attained state-of-the-art performance. GAN can capture, duplicate, and analyze variations in a dataset since it takes two fundamental structure pieces (multiple neural networks) that compete with one another, as shown in Figure 6 [16]. Both of the networks are referred to as (Generators & Discriminators), while the discriminator neural net judges the validity of the created images, the generator neural network assists in the creation of new instances. The discriminator penalizes the generator for providing implausible results by determining whether or not each instance of data it analyzes belongs to the real training set. Insufficient data is a major barrier to the development of successful deep neural network models. But GANs are the answer for data augmentation in computer vision to reduce model overfitting, they generated realistic images that depart from the initial training data[17].

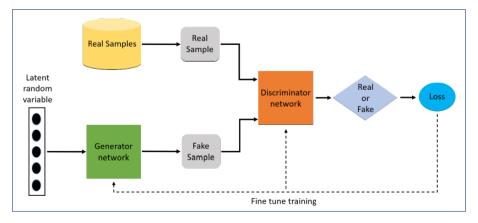


Figure 6. Generative Adversarial Network architecture.

# 3. Deep learning frameworks

- TensorFlow-supported languages include Python, C++, and R; created by Google Brain, it enables us to use both CPUs and GPUs for our deep learning models. A GPU code for image categorization can run up to twice as quickly as a CPU equivalent[18].
- Keras is an API, based on TensorFlow and developed in Python. It allows for quick experimentation and operates on both CPUs and GPUs and supports both CNNs and RNNs[18].
- PyTorch is capable of both doing tensor computations and creating deep neural networks. Tensor computations are offered via the Python-based library PyTorch using PyTorch and you can build computational graphs [18].
- Caffe was created by Caffe Yangqing Jiaadditionally, It's open-source. Regarding processing speed and picture learning, Caffe is superior to other frameworks, we may access pre-trained models through the Caffe Model Zoo framework which enables us to handle a variety of challenges[18].
- Deeplearning4 It is more effective than Python because it is implemented in Java, working with multi-dimensional arrays or tensors is possible thanks to the ND4J tensor package that Deeplearn-ing4j uses. It supports both CPUs and GPUs, images, CSV, and plaintext are all supported by Deeplearning4j[18].

# 4. Deep learning applications

In this section, we covered the techniques of deep learning networks, and their various applications are summarized in Table 1. And the different application fields of deep learning techniques with the methodology used and the purpose of that methodology is summarized in Table 2.

Networks	Applications Domains	Year	Researcher	
Multilayer Perceptron	Detection of liner surface defects in solid rocket motors	2020	Simões et al.[19]	
Networks	Prediction of financial distress	2022	Wu et al.[20]	
(MLP)	Prediction of the rainfall	2022	Hunasigi et al. [21]	
	Future prediction	2018	Olawoyin et al.[22]	
	Analysis of Patients suffering from influenza	2016	Sarangi et al.[23]	
	Polyjet 3d printing: predicting color	2022	Wei et al. [24]	
	Deepfake detection	2022	Kolagati et al.[25]	
	Intelligently preparing for bankruptcy	2022	Brenes et al.[26]	
	Image processing to ascertain the age and gender	2018	Avuçlu et al.[27]	
	3D shape retrieval	2017	Avuçlu et al.[28]	
	Purchases in B2B E-commerce	2017	Vincent et al. [29]	
Convolutional	Visualizing a sentiment classifier	2020	Chawla et al. [30]	
Neural Networks	Covid-19 automatic detection and classification using X-Ray	2021	Thakur et al. [31]	
(CNNs or	Differentiating artifacts 2021 Real et al.			
ConvNets)	Drone recognition using radar	2022	Garcia et al. [33]	
	Distraction detection for drivers automatically	2022	Uzzol et al.[34]	
	Classification of remote sensing scenes	2016	Nogueira et al.[35]	
	Segmentation of medical images 3D(CNN)	2021	Niyas et al.[36]	
	Air quality forecast	2021	Chauhan et al.[37]	
	A brain capable of MRI segmentation	2020	Thyreau et al. [38]	
	Automatic inspection for defects in CFRP thermograms	2019	Saeed et al.[39]	
CNN Pre-Trained	Efficientnet-B3: automatic Covid-19 screening uncertainty	2022	Gour et al.[40]	
Models	Efficientnet: classification of land cover images	2021	Papoutsis et al.[41]	
	Resnet-34: diabetes retinopathy diagnosis	2021	Moosawi et al. [42]	
	Alexnet & Googlenet: Recognition of handwritten characters	2020	Mohammed et al[43]	

Table 1: Summary of network applications and articles of researchers.

	Vgg-16: recognizing student behavior in the classroom	2021	Abdallah et al. [44]
	Alexnet, Googlenet: system of face recognition	2021	Alhanaee et al. [45]
	Vgg16, Vgg19, Alexnet, InceptionV3: Recognizing	2021	Islam et al. [46]
	multiclass sign language words for the deaf and dumb InceptionV3, Mobilenet: mapping tree species in RGB	2022	Carvalho et al.[47]
	pictures	2020	
	Vgg-16: recognizing hockey activities	2020	Rangasamy et al. [48]
	Vgg: classification of multi-crop leaf disease images	2020	Paymode et al. [49]
	Mobilenet-V1 & Resnet: vehicle type classification	2022	Taqiyuddin et al.[50]
Recurrent	System for detecting intrusions	2023	Kasongo[51]
Neural	Text sentiment analysis	2022	Onan [52]
Networks	Prediction of the Covid-19 mortality risk change	2023	Villegas et al.[53]
(RNN)	Time series prediction for pore-water pressure	2021	Wei et al.[54]
	Arrhythmia classification using the ECG	2022	Falaschetti et al.[55]
	Methodology for predicting crop rotation	2023	Dupuis et al. [56]
	E-commerce review classification and statistical analysis	2018	Agarap [57]
	Anomaly detection in data from aircraft	2016	Nanduri et al. [58]
	Botnet detection for smart homes	2021	Popoola et al. [59]
Long Short-	Identifying dangerous construction conduct	2021	Kong et al.[60]
Term Memory	intelligent power distribution	2021	Sahu et al. [61]
(LSTM)	Forecasting the weather	2018	Salman et al. [62]
	groundwater quality forecasting for irrigation	2023	Docheshmeh et
	De sitiser Consid 10 former ating	2022	al.[63]
	Positive Covid-19 forecasting	2023	Sunjaya et al. [64]
	AI for Covid-19 virus reverse engineering	2021	Haimed et al.[65]
	Robot cell predictive maintenance application	2022	Joseph et al.[66]
	Prediction of air pollution	2022	Drewil et al. [67]
	Flood forecasting Malware detection for android	2019 2018	Le et al. [68]
	Malware detection for android	2018	Vinayakumar et al.[69]
	Sentiment analysis of text	2016	Li et al.[70]
Autoencoders	Age estimation	2018	Zaghbani et al.[71]
		0000	
(AE)	Diagnostics for faults in industrial processes	2022	Qian et al. [72]
(AE)	Diagnostics for faults in industrial processes Forecasting of power prices	2022 2021	Qian et al. [72] Demir et al. [73]
(AE)			
(AE)	Forecasting of power prices	2021	Demir et al. [73]
(AE)	Forecasting of power prices Stock prediction	2021 2022	Demir et al. [73] Wu et al.[74]
(AE)	Forecasting of power prices Stock prediction Automotive audio anomaly detection	2021 2022 2021	Demir et al. [73] Wu et al.[74] Pereira et al.[75] Chen et al.[76]
(AE)	Forecasting of power prices Stock prediction Automotive audio anomaly detection Forecast the course of Alzheimer's disease	2021 2022 2021 2022	Demir et al. [73] Wu et al.[74] Pereira et al.[75]
(AE)	Forecasting of power prices Stock prediction Automotive audio anomaly detection Forecast the course of Alzheimer's disease Detecting trespass within the vehicle	2021 2022 2021 2022 2022	Demir et al. [73] Wu et al.[74] Pereira et al.[75] Chen et al.[76] Hoang et al.[77]
(AE) Generative	Forecasting of power prices Stock prediction Automotive audio anomaly detection Forecast the course of Alzheimer's disease Detecting trespass within the vehicle Identifying and fixing faults in building automation	2021 2022 2021 2022 2022 2022 2021	Demir et al. [73] Wu et al.[74] Pereira et al.[75] Chen et al.[76] Hoang et al.[77] Choi et al. [78]
	Forecasting of power pricesStock predictionAutomotive audio anomaly detectionForecast the course of Alzheimer's diseaseDetecting trespass within the vehicleIdentifying and fixing faults in building automationMonitoring the health of machinery	2021 2022 2021 2022 2022 2022 2021 2021	Demir et al. [73] Wu et al.[74] Pereira et al.[75] Chen et al.[76] Hoang et al.[77] Choi et al. [78] Ye et al. [79]
Generative	Forecasting of power pricesStock predictionAutomotive audio anomaly detectionForecast the course of Alzheimer's diseaseDetecting trespass within the vehicleIdentifying and fixing faults in building automationMonitoring the health of machineryImage Inpainting	2021 2022 2021 2022 2022 2021 2021 2021	Demir et al. [73] Wu et al.[74] Pereira et al.[75] Chen et al.[76] Hoang et al.[77] Choi et al. [78] Ye et al. [79] Qin et al. [80]
Generative Adversarial	Forecasting of power pricesStock predictionAutomotive audio anomaly detectionForecast the course of Alzheimer's diseaseDetecting trespass within the vehicleIdentifying and fixing faults in building automationMonitoring the health of machineryImage InpaintingReconstruction of remote sensing images	2021 2022 2021 2022 2022 2021 2021 2021	Demir et al. [73] Wu et al.[74] Pereira et al.[75] Chen et al.[76] Hoang et al.[77] Choi et al. [78] Ye et al. [79] Qin et al. [80] Zhu et al. [81]
Generative Adversarial Networks	Forecasting of power pricesStock predictionAutomotive audio anomaly detectionForecast the course of Alzheimer's diseaseDetecting trespass within the vehicleIdentifying and fixing faults in building automationMonitoring the health of machineryImage InpaintingReconstruction of remote sensing imagesUsing X-ray pictures to identify Covid-19 & pneumonia	2021 2022 2021 2022 2022 2021 2021 2021	Demir et al. [73] Wu et al.[74] Pereira et al.[75] Chen et al.[76] Hoang et al.[77] Choi et al. [78] Ye et al. [79] Qin et al. [80] Zhu et al. [81] Motamed et al. [82]
Generative Adversarial Networks	Forecasting of power pricesStock predictionAutomotive audio anomaly detectionForecast the course of Alzheimer's diseaseDetecting trespass within the vehicleIdentifying and fixing faults in building automationMonitoring the health of machineryImage InpaintingReconstruction of remote sensing imagesUsing X-ray pictures to identify Covid-19 & pneumoniaPicture steganography across WSNMonitoring water quality in water delivery networksProduction of artificial demand statistics for power	2021 2022 2021 2022 2022 2021 2021 2021	Demir et al. [73] Wu et al.[74] Pereira et al.[75] Chen et al.[76] Hoang et al.[77] Choi et al. [78] Ye et al. [79] Qin et al. [80] Zhu et al. [81] Motamed et al. [82] Ambika et al.[83]
Generative Adversarial Networks	Forecasting of power prices Stock prediction Automotive audio anomaly detection Forecast the course of Alzheimer's disease Detecting trespass within the vehicle Identifying and fixing faults in building automation Monitoring the health of machinery Image Inpainting Reconstruction of remote sensing images Using X-ray pictures to identify Covid-19 & pneumonia Picture steganography across WSN Monitoring water quality in water delivery networks Production of artificial demand statistics for power users	2021 2022 2021 2022 2022 2021 2021 2021	Demir et al. [73] Wu et al.[74] Pereira et al.[75] Chen et al.[76] Hoang et al.[77] Choi et al. [78] Ye et al. [79] Qin et al. [80] Zhu et al. [81] Motamed et al. [82] Ambika et al.[83] Li et al. [84] Yilmaz et al. [85]
Generative Adversarial Networks	Forecasting of power pricesStock predictionAutomotive audio anomaly detectionForecast the course of Alzheimer's diseaseDetecting trespass within the vehicleIdentifying and fixing faults in building automationMonitoring the health of machineryImage InpaintingReconstruction of remote sensing imagesUsing X-ray pictures to identify Covid-19 & pneumoniaPicture steganography across WSNMonitoring water quality in water delivery networksProduction of artificial demand statistics for powerusersNoise reduction for optical coherence	2021 2022 2021 2022 2022 2021 2021 2021	Demir et al. [73] Wu et al.[74] Pereira et al.[75] Chen et al.[76] Hoang et al.[77] Choi et al. [78] Ye et al. [79] Qin et al. [80] Zhu et al. [81] Motamed et al. [82] Ambika et al.[83] Li et al. [84] Yilmaz et al. [85] Chen et al. [86]
Generative Adversarial Networks	Forecasting of power prices Stock prediction Automotive audio anomaly detection Forecast the course of Alzheimer's disease Detecting trespass within the vehicle Identifying and fixing faults in building automation Monitoring the health of machinery Image Inpainting Reconstruction of remote sensing images Using X-ray pictures to identify Covid-19 & pneumonia Picture steganography across WSN Monitoring water quality in water delivery networks Production of artificial demand statistics for power users	2021 2022 2021 2022 2022 2021 2021 2021	Demir et al. [73] Wu et al.[74] Pereira et al.[75] Chen et al.[76] Hoang et al.[77] Choi et al. [78] Ye et al. [79] Qin et al. [80] Zhu et al. [81] Motamed et al. [82] Ambika et al.[83] Li et al. [84] Yilmaz et al. [85]

<b>D' 11</b>					
Field	Methodology	Target Objects	Ref.		
Computer Vision	CNN	Robotics & self-driving car deployment	[90]		
&	Alexnet, Vgg-16, Googlenet, and Resnet.	Segmentation of Images and Videos	[91]		
Image Classification	CNN, RNN, LSTM, GAN and Auto-Encoders	Recognition of Biometrics (Face, Iris, Fingerprint, Palmprint recognition)	[92]		
	Pre-trained CNN models	Scene classification using remote sensing images	[93]		
	LSTM & RNN	Classifying of images and texts	[94]		
Medical Applications	CNN models (Resnet18, Resnet50, Vgg16, Resnet101, Vgg19) and (SVM)	X-Ray images for Covid-19 detection	[95]		
	CNN	Diagnoses of diabetic retinopathy	[96]		
	CNN & Vgg16 for feature extractor	MRI scans for Alzheimer's detection	[97]		
Text Classification	CNN & Alexnet model	Classification of poisonous comments	[98]		
Prediction	Neural Networks	Modeling of Energy Consumption	[99]		
	YOLO V2	Goal coordinates by RGB-D camera	[100]		
	MLP & LSTM	Prediction of Web Navigation (WNP)	[101]		
Natural Language Processing (NLP)	Bert, Bidirectional LSTM, K-NN, And NB (Naive Bayes)	Email spam detection	[102]		
	Bert (bidirectional encoder representations from transformers) for question-answering and LSTM for machine translation.	Providing Remote Education for Schools	[103]		
	Multilayer perceptron (MLP)	Recognition of Voice Gender	[104]		
Agricultural	GAN and vision transformers (VIT)	Automation in agriculture	[16]		
Applications	Resnet50 for image classification	Disease detection in plants	[105]		
Network	CNN, LSTM, and InceptionV3	Malware classification	[106]		
Security	CNN and LSTM	Attack detection on the IOT	[61]		
Image Clustering	Pre-trained CNN features	Complicated natural image clustering	[107]		
Image Recognition	(CNN) object detection & YOLO	Road fault detection	[108]		
Construction Industry	CNN, LSTM, and RNN	Facility management and upkeep for ventilation, heating, air conditioning	[109]		
Classification of Vertices and Graphs	CNN & (LSTM)	Classification of dynamic graphs	[110]		

#### **Table 2:** Summary of applications field and deep learning techniques.

#### 5. CONCLUSION

Deep learning techniques have shown to be important and useful in many fields since they assist specialists and clients in making decisions, save time and effort, and help with choice-making. One of the important benefits of deep learning is its capacity for autonomous instruction and feature extraction from data, which is particularly useful for tasks such as image classification or speech recognition. This is achieved through the use of convolutional neural networks (CNNs), recurrent neural networks (RNNs), autoencoders (AE), generative adversarial networks (GANs), and Long Short-Term Memory(LSTM). The healthcare, financial, and advertising sectors are just a few of the many that can benefit from deep learning. It could radically alter how we tackle difficult problems. It will be important to keep up with the latest developments in the field of deep learning as new methods and applications emerge. Deep learning has the potential to revolutionize how researchers, engineers, and business professionals do their work and open new avenues for advancement. When applied to solving difficult problems and making accurate predictions from massive datasets, deep learning has proven to be an invaluable tool. More and more creative uses of deep learning are likely to emerge in the years ahead as research in this area continues to develop.

This study's objective is to highlight the significance of deep learning research over the past few decades, a period that has seen the emergence of many new fields that can benefit from deep learning. Several recent publications' contents were briefly summarized, and their respective implementations were presented in tables along with a brief explanation of deep neural networks and their uses. The purpose of this article is to draw attention to the most consequential deep learning applications that have recently seen significant uptake and are expected to feature prominently in future research. These examples can serve as a springboard for further research by the reader.

#### References

- M. M. Mijwil, D. Salim Mutar, E. Sh Mahmood, M. Gök, S. Uzun, and R. Doshi, "Deep Learning Applications and Their Worth: A Short Review," 2022. [Online]. Available: www.ajouronline.com
- [2] J. Schmidhuber, "Deep Learning in Neural Networks: An Overview," International Conference on Modeling, Simulation and Optimization Technologies and Applications (MSOTA2016), vol. 61, p. pp.85-117, Apr. 2015, doi: 10.1016/j.neunet.2014.09.003.
- [3] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *J Big Data*, vol. 8, no. 1, Dec. 2021, doi: 10.1186/s40537-021-00444-8.
- [4] S. Dong, P. Wang, and K. Abbas, "A survey on deep learning and its applications," *Computer Science Review*, vol. 40. Elsevier Ireland Ltd, May 01, 2021. doi: 10.1016/j.cosrev.2021.100379.
- [5] X. Liu et al., "Privacy and Security Issues in Deep Learning: A Survey," IEEE Access, vol. 9. Institute of Electrical and Electronics Engineers Inc., pp. 4566–4593, 2021. doi: 10.1109/ACCESS.2020.3045078.
- [6] A. Mathew, P. Amudha, and S. Sivakumari, "Deep learning techniques: an overview," in Advances in Intelligent Systems and Computing, Springer, 2021, pp. 599–608. doi: 10.1007/978-981-15-3383-9\_54.
- [7] S. A, "Studying the Effect of Activation Function on Classification Accuracy Using Deep Artificial Neural Networks," *Journal of Remote Sensing & GIS*, vol. 06, no. 03, 2017, doi: 10.4172/2469-4134.1000203.
- [8] H. Gu, Y. Wang, S. Hong, and G. Gui, "Blind channel identification aided generalized automatic modulation recognition based on deep learning," *IEEE Access*, vol. 7, pp. 110722–110729, 2019, doi: 10.1109/ACCESS.2019.2934354.
- [9] S. Tulasi Krishna, "Deep Learning and Transfer Learning Approaches for Image Classification." [Online]. Available: https://www.researchgate.net/publication/333666150
- [10] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, "A survey of the recent architectures of deep convolutional neural networks," *Artif Intell Rev*, vol. 53, no. 8, pp. 5455–5516, Dec. 2020, doi: 10.1007/s10462-020-09825-6.
- [11] S. A. Sanchez, H. J. Romero, and A. D. Morales, "A review: Comparison of performance metrics of pretrained models for object detection using the TensorFlow framework," in *IOP Conference Series: Materials Science and Engineering*, Institute of Physics Publishing, Jun. 2020. doi: 10.1088/1757-899X/844/1/012024.
- [12] M. Tan and Q. v Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks."
- [13] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553. Nature Publishing Group, pp. 436–444, May 27, 2015. doi: 10.1038/nature14539.
- [14] A. Shrestha and A. Mahmood, "Review of deep learning algorithms and architectures," *IEEE Access*, vol. 7. Institute of Electrical and Electronics Engineers Inc., pp. 53040–53065, 2019. doi: 10.1109/ACCESS.2019.2912200.
- [15] S. S., J. I. Zong Chen, and S. Shakya, "Survey on Neural Network Architectures with Deep Learning," *Journal of Soft Computing Paradigm*, vol. 2, no. 3, pp. 186–194, Jul. 2020, doi: 10.36548/jscp.2020.3.007.
- [16] V. G. Dhanya et al., "Deep learning based computer vision approaches for smart agricultural applications," Artificial Intelligence in Agriculture, vol. 6. KeAi Communications Co., pp. 211–229, Jan. 01, 2022. doi: 10.1016/j.aiia.2022.09.007.
- [17] A. Dash, J. Ye, and G. Wang, "A review of Generative Adversarial Networks (GANs) and its applications in a wide variety of disciplines -- From Medical to Remote Sensing," Oct. 2021, [Online]. Available: http://arxiv.org/abs/2110.01442
- [18] S. Sakib, A. 1#, A. Jawad, K. 2@, and H. Ahmed, "An Overview of Convolutional Neural Network: Its Architecture and Applications," 2019, doi: 10.20944/preprints201811.0546.v4.
- [19] L. F. Simões Hoffmann, F. C. Parquet Bizarria, and J. W. Parquet Bizarria, "Detection of liner surface defects in solid rocket motors using multilayer perceptron neural networks," *Polym Test*, vol. 88, Aug. 2020, doi: 10.1016/j.polymertesting.2020.106559.
- [20] D. Wu, X. Ma, and D. L. Olson, "Financial distress prediction using integrated Z-score and multilayer perceptron neural networks," *Decis Support Syst*, vol. 159, Aug. 2022, doi: 10.1016/j.dss.2022.113814.
- [21] P. Hunasigi, S. Jedhe, M. Mane, and V. Patil-Shinde, "Multilayer perceptron neural network based models for prediction of the rainfall and reference crop evapotranspiration for sub-humid climate of Dapoli, Ratnagiri District, India," Acta Ecologica Sinica, Feb. 2022, doi: 10.1016/j.chnaes.2022.09.004.
- [22] A. Olawoyin and Y. Chen, "Predicting the future with artificial neural network," in *Procedia Computer Science*, Elsevier B.V., 2018, pp. 383–392. doi: 10.1016/j.procs.2018.10.300.
- [23] L. Sarangi, M. N. Mohanty, and S. Pattanayak, "Design of MLP Based Model for Analysis of Patient Suffering from Influenza," in Procedia Computer Science, Elsevier B.V., 2016, pp. 396–403. doi: 10.1016/j.procs.2016.07.396.
- [24] X. Wei, N. Zou, L. Zeng, and Z. Pei, "PolyJet 3D printing: Predicting color by multilayer perceptron neural network," Annals of 3D Printed Medicine, vol. 5, p. 100049, Mar. 2022, doi: 10.1016/j.stlm.2022.100049.
- [25] S. Kolagati, T. Priyadharshini, and V. Mary Anita Rajam, "Exposing deepfakes using a deep multilayer perceptron convolutional neural network model," *International Journal of Information Management Data Insights*, vol. 2, no. 1, Apr. 2022, doi: 10.1016/j.jjimei.2021.100054.
- [26] R. F. Brenes, A. Johannssen, and N. Chukhrova, "An intelligent bankruptcy prediction model using a multilayer perceptron," *Intelligent Systems with Applications*, vol. 16, Nov. 2022, doi: 10.1016/j.iswa.2022.200136.
- [27] E. Avuçlu and F. Başçiftçi, "New approaches to determine age and gender in image processing techniques using multilayer perceptron neural network," *Applied Soft Computing Journal*, vol. 70, pp. 157–168, Sep. 2018, doi: 10.1016/j.asoc.2018.05.033.

- [28] W. Zhou and J. Jia, "A learning framework for shape retrieval based on multilayer perceptrons," *Pattern Recognit Lett*, vol. 117, pp. 119–130, Jan. 2019, doi: 10.1016/j.patrec.2018.09.005.
- [29] O. R. Vincent, A. S. Makinde, and A. T. Akinwale, "A cognitive buying decision-making process in B2B e-commerce using Analytic-MLP," *Electron Commer Res Appl*, vol. 25, pp. 59–69, Sep. 2017, doi: 10.1016/j.elerap.2017.08.002.
- [30] P. Chawla, S. Hazarika, and H. W. Shen, "Token-wise sentiment decomposition for ConvNet: Visualizing a sentiment classifier," Visual Informatics, vol. 4, no. 2, pp. 132–141, Jun. 2020, doi: 10.1016/j.visinf.2020.04.006.
- [31] S. Thakur and A. Kumar, "X-ray and CT-scan-based automated detection and classification of covid-19 using convolutional neural networks (CNN)," *Biomed Signal Process Control*, vol. 69, Aug. 2021, doi: 10.1016/j.bspc.2021.102920.
- [32] R. Real, J. Gopsill, D. Jones, C. Snider, and B. Hicks, "Distinguishing artefacts: Evaluating the saturation point of convolutional neural networks," in Procedia CIRP, Elsevier B.V., 2021, pp. 385–390. doi: 10.1016/j.procir.2021.05.089.
- [33] A. J. Garcia, A. Aouto, J. M. Lee, and D. S. Kim, "CNN-32DC: An improved radar-based drone recognition system based on Convolutional Neural Network," ICT Express, Dec. 2022, doi: 10.1016/j.icte.2022.04.012.
- [34] M. Uzzol Hossain, M. Ataur Rahman, M. Manowarul Islam, A. Akhter, M. Ashraf Uddin, and B. Kumar Paul, "Automatic driver distraction detection using deep convolutional neural networks," *Intelligent Systems with Applications*, vol. 14, p. 75, 2022, doi: 10.1016/j.iswa.2022.20.
- [35] K. Nogueira, O. A. B. Penatti, and J. A. dos Santos, "Towards Better Exploiting Convolutional Neural Networks for Remote Sensing Scene Classification," Feb. 2016, doi: 10.1016/j.patcog.2016.07.001.
- [36] S. Niyas, S. J. Pawan, M. A. Kumar, and J. Rajan, "Medical Image Segmentation with 3D Convolutional Neural Networks: A Survey," Aug. 2021, [Online]. Available: http://arxiv.org/abs/2108.08467
- [37] R. Chauhan, H. Kaur, and B. Alankar, "Air Quality Forecast using Convolutional Neural Network for Sustainable Development in Urban Environments," Sustain Cities Soc, vol. 75, Dec. 2021, doi: 10.1016/j.scs.2021.103239.
- [38] B. Thyreau and Y. Taki, "Learning a cortical parcellation of the brain robust to the MRI segmentation with convolutional neural networks," *Med Image Anal*, vol. 61, Apr. 2020, doi: 10.1016/j.media.2020.101639.
- [39] N. Saeed, N. King, Z. Said, and M. A. Omar, "Automatic defects detection in CFRP thermograms, using convolutional neural networks and transfer learning," *Infrared Phys Technol*, vol. 102, Nov. 2019, doi: 10.1016/j.infrared.2019.103048.
- [40] M. Gour and S. Jain, "Uncertainty-aware convolutional neural network for COVID-19 X-ray images classification," Comput Biol Med, vol. 140, Jan. 2022, doi: 10.1016/j.compbiomed.2021.105047.
- [41] I. Papoutsis, N.-I. Bountos, A. Zavras, D. Michail, and C. Tryfonopoulos, "Efficient deep learning models for land cover image classification," Nov. 2021, doi: 10.1016/j.isprsjprs.2022.11.012.
- [42] N. M. Al-Moosawi and R. S. Khudeyer, "ResNet-34/DR: A Residual Convolutional Neural Network for the Diagnosis of Diabetic Retinopathy," Informatica (Slovenia), vol. 45, no. 7, pp. 115–124, 2021, doi: 10.31449/inf.v45i7.3774.
- [43] K. O. Mohammed Aarif and S. Poruran, "OCR-Nets: Variants of Pre-trained CNN for Urdu Handwritten Character Recognition via Transfer Learning," in *Procedia Computer Science*, Elsevier B.V., 2020, pp. 2294–2301. doi: 10.1016/j.procs.2020.04.248.
- [44] T. ben Abdallah, I. Elleuch, and R. Guermazi, "Student behavior recognition in classroom using deep transfer learning with VGG-16," in Procedia Computer Science, Elsevier B.V., 2021, pp. 951–960. doi: 10.1016/j.procs.2021.08.098.
- [45] K. Alhanaee, M. Alhammadi, N. Almenhali, and M. Shatnawi, "Face recognition smart attendance system using deep transfer learning," in Procedia Computer Science, Elsevier B.V., 2021, pp. 4093–4102. doi: 10.1016/j.procs.2021.09.184.
- [46] M. M. Islam, M. R. Uddin, M. N. AKhtar, and K. M. R. Alam, "Recognizing multiclass Static Sign Language words for deaf and dumb people of Bangladesh based on transfer learning techniques," *Inform Med Unlocked*, vol. 33, Jan. 2022, doi: 10.1016/j.imu.2022.101077.
- [47] M. de A. Carvalho *et al.*, "A deep learning-based mobile application for tree species mapping in RGB images," *International Journal of Applied Earth Observation and Geoinformation*, vol. 114, Nov. 2022, doi: 10.1016/j.jag.2022.103045.
- [48] K. Rangasamy, M. A. As'ari, N. A. Rahmad, and N. F. Ghazali, "Hockey activity recognition using pre-trained deep learning model," *ICT Express*, vol. 6, no. 3, pp. 170–174, Sep. 2020, doi: 10.1016/j.icte.2020.04.013.
- [49] A. S. Paymode and V. B. Malode, "Transfer Learning for Multi-Crop Leaf Disease Image Classification using Convolutional Neural Network VGG," Artificial Intelligence in Agriculture, vol. 6, pp. 23–33, Jan. 2022, doi: 10.1016/j.aiia.2021.12.002.
- [50] M. Taqiyuddin, Y. E. Windarto, W. A. Syafei, I. P. Windasari, and A. B. Prasetijo, "Accuracy Improvement of CNN MobileNet-V1 and Residual Network 50 Layers Models using Adam setting for Car Type Classification," in 2022 International Symposium on Electronics and Smart Devices (ISESD), IEEE, Nov. 2022, pp. 1–7. doi: 10.1109/ISESD56103.2022.9980771.
- [51] S. M. Kasongo, "A deep learning technique for intrusion detection system using a Recurrent Neural Networks based framework," *Comput Commun*, vol. 199, pp. 113–125, Feb. 2023, doi: 10.1016/j.comcom.2022.12.010.
- [52] A. Onan, "Bidirectional convolutional recurrent neural network architecture with group-wise enhancement mechanism for text sentiment classification," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 5, pp. 2098–2117, May 2022, doi: 10.1016/j.jksuci.2022.02.025.
- [53] M. Villegas et al., "Predicting the evolution of COVID-19 mortality risk: A Recurrent Neural Network approach," Computer Methods and Programs in Biomedicine Update, vol. 3, p. 100089, 2023, doi: 10.1016/j.cmpbup.2022.100089.
- [54] X. Wei, L. Zhang, H. Q. Yang, L. Zhang, and Y. P. Yao, "Machine learning for pore-water pressure time-series prediction: Application of recurrent neural networks," *Geoscience Frontiers*, vol. 12, no. 1, pp. 453–467, Jan. 2021, doi: 10.1016/j.gsf.2020.04.011.
- [55] L. Falaschetti, M. Alessandrini, G. Biagetti, P. Crippa, and C. Turchetti, "ECG-Based Arrhythmia Classification using Recurrent Neural Networks in Embedded Systems," *Procedia Comput Sci*, vol. 207, pp. 3479–3487, 2022, doi: 10.1016/j.procs.2022.09.406.
- [56] A. Dupuis, C. Dadouchi, and B. Agard, "Methodology for multi-temporal prediction of crop rotations using recurrent neural networks," *Smart Agricultural Technology*, vol. 4, Aug. 2023, doi: 10.1016/j.atech.2022.100152.
- [57] A. F. Agarap, "Statistical Analysis on E-Commerce Reviews, with Sentiment Classification using Bidirectional Recurrent Neural Network (RNN)," May 2018, [Online]. Available: http://arxiv.org/abs/1805.03687
- [58] A. , Nanduri and L. & Sherry, "Anomaly detection in aircraft data using Recurrent Neural Networks (RNN)," Integrated Communications Navigation and Surveillance (ICNS), vol. 2016, April, pp. 5C2-1, 2016.
- [59] S. I. Popoola, B. Adebisi, M. Hammoudeh, H. Gacanin, and G. Gui, "Stacked recurrent neural network for botnet detection in smart homes," *Computers and Electrical Engineering*, vol. 92, Jun. 2021, doi: 10.1016/j.compeleceng.2021.107039.
- [60] T. Kong, W. Fang, P. E. D. Love, H. Luo, S. Xu, and H. Li, "Computer vision and long short-term memory: Learning to predict unsafe behaviour in construction," Advanced Engineering Informatics, vol. 50, Oct. 2021, doi: 10.1016/j.aei.2021.101400.
- [61] A. K. Sahu, S. Sharma, M. Tanveer, and R. Raja, "Internet of Things attack detection using hybrid Deep Learning Model," *Comput Commun*, vol. 176, pp. 146–154, Aug. 2021, doi: 10.1016/j.comcom.2021.05.024.

- [62] A. G. Salman, Y. Heryadi, E. Abdurahman, and W. Suparta, "Single Layer & Multi-layer Long Short-Term Memory (LSTM) Model with Intermediate Variables for Weather Forecasting," in *Procedia Computer Science*, Elsevier B.V., 2018, pp. 89–98. doi: 10.1016/j.procs.2018.08.153.
- [63] A. Docheshmeh Gorgij, G. Askari, A. A. Taghipour, M. Jami, and M. Mirfardi, "Spatiotemporal Forecasting of the Groundwater Quality for Irrigation Purposes, Using Deep Learning Method: Long Short-Term Memory (LSTM)," *Agric Water Manag*, vol. 277, p. 108088, Mar. 2023, doi: 10.1016/j.agwat.2022.108088.
- [64] B. A. Sunjaya, S. D. Permai, and A. A. S. Gunawan, "Forecasting of Covid-19 positive cases in Indonesia using long short-term memory (LSTM)," Procedia Comput Sci, vol. 216, pp. 177–185, 2023, doi: 10.1016/j.procs.2022.12.125.
- [65] A. M. A. Haimed, T. Saba, A. Albasha, A. Rehman, and M. Kolivand, "Viral reverse engineering using Artificial Intelligence and big data COVID-19 infection with Long Short-term Memory (LSTM)," *Environ Technol Innov*, vol. 22, May 2021, doi: 10.1016/j.eti.2021.101531.
- [66] D. Joseph, T. Gallege, E. T. Bekar, C. Dudas, and A. Skoogh, "A Predictive Maintenance Application for A Robot Cell using LSTM Model," *IFAC-PapersOnLine*, vol. 55, no. 19, pp. 115–120, 2022, doi: 10.1016/j.ifacol.2022.09.193.
- [67] G. I. Drewil and R. J. Al-Bahadili, "Air pollution prediction using LSTM deep learning and metaheuristics algorithms," *Measurement: Sensors*, vol. 24, p. 100546, Dec. 2022, doi: 10.1016/j.measen.2022.100546.
- [68] X. H. Le, H. V. Ho, G. Lee, and S. Jung, "Application of Long Short-Term Memory (LSTM) neural network for flood forecasting," Water (Switzerland), vol. 11, no. 7, 2019, doi: 10.3390/w11071387.
- [69] R. Vinayakumar, K. P. Soman, P. Poornachandran, and S. Sachin Kumar, "Detecting Android malware using Long Short-term Memory (LSTM)," in *Journal of Intelligent and Fuzzy Systems*, IOS Press, 2018, pp. 1277–1288. doi: 10.3233/JIFS-169424.
- [70] Li D. & and J. Qian, "Text sentiment analysis based on long short-term memory," International Conference on Computer Communication and the Internet (ICCCI), vol. 2016, October, pp. 471–475, 2016.
- [71] S. Zaghbani, N. Boujneh, and M. S. Bouhlel, "Age estimation using deep learning," *Computers and Electrical Engineering*, vol. 68, pp. 337–347, May 2018, doi: 10.1016/j.compeleceng.2018.04.012.
- [72] J. Qian, Z. Song, Y. Yao, Z. Zhu, and X. Zhang, "A review on autoencoder based representation learning for fault detection and diagnosis in industrial processes," *Chemometrics and Intelligent Laboratory Systems*, vol. 231, p. 104711, Dec. 2022, doi: 10.1016/j.chemolab.2022.104711.
- [73] S. Demir, K. Mincev, K. Kok, and N. G. Paterakis, "Data augmentation for time series regression: Applying transformations, autoencoders and adversarial networks to electricity price forecasting," *Appl Energy*, vol. 304, Dec. 2021, doi: 10.1016/j.apenergy.2021.117695.
- [74] D. Wu, X. Wang, and S. Wu, "A hybrid framework based on extreme learning machine, discrete wavelet transform, and autoencoder with feature penalty for stock prediction," *Expert Syst Appl*, vol. 207, Nov. 2022, doi: 10.1016/j.eswa.2022.118006.
- [75] P. J. Pereira *et al.*, "Using deep autoencoders for in-vehicle audio anomaly detection," in *Procedia Computer Science*, Elsevier B.V., 2021, pp. 298–307. doi: 10.1016/j.procs.2021.08.031.
- [76] L. Chen, A. J. Saykin, B. Yao, and F. Zhao, "Multi-task deep autoencoder to predict Alzheimer's disease progression using temporal DNA methylation data in peripheral blood," *Comput Struct Biotechnol J*, vol. 20, pp. 5761–5774, Jan. 2022, doi: 10.1016/j.csbj.2022.10.016.
- [77] T. N. Hoang and D. Kim, "Detecting in-vehicle intrusion via semi-supervised learning-based convolutional adversarial autoencoders," *Vehicular Communications*, vol. 38, Dec. 2022, doi: 10.1016/j.vehcom.2022.100520.
- [78] Y. Choi and S. Yoon, "Autoencoder-driven fault detection and diagnosis in building automation systems: Residual-based and latent spacebased approaches," *Build Environ*, vol. 203, Oct. 2021, doi: 10.1016/j.buildenv.2021.108066.
- [79] Z. Ye and J. Yu, "Health condition monitoring of machines based on long short-term memory convolutional autoencoder," *Appl Soft Comput*, vol. 107, Aug. 2021, doi: 10.1016/j.asoc.2021.107379.
- [80] Z. Qin, Q. Zeng, Y. Zong, and F. Xu, "Image inpainting based on deep learning: A review," *Displays*, vol. 69, Sep. 2021, doi: 10.1016/j.displa.2021.102028.
- [81] F. Zhu, C. Wang, B. Zhu, C. Sun, and C. Qi, "An improved generative adversarial networks for remote sensing image super-resolution reconstruction via multi-scale residual block," *Egyptian Journal of Remote Sensing and Space Science*, vol. 26, no. 1, pp. 151–160, Feb. 2023, doi: 10.1016/j.ejrs.2022.12.008.
- [82] S. Motamed, P. Rogalla, and F. Khalvati, "Data augmentation using Generative Adversarial Networks (GANs) for GAN-based detection of Pneumonia and COVID-19 in chest X-ray images," *Inform Med Unlocked*, vol. 27, Jan. 2021, doi: 10.1016/j.imu.2021.100779.
- [83] Ambika, Virupakshappa, and S. Veerashetty, "Secure communication over wireless sensor network using image steganography with generative adversarial networks," *Measurement: Sensors*, vol. 24, Dec. 2022, doi: 10.1016/j.measen.2022.100452.
- [84] Z. Li, H. Liu, C. Zhang, and G. Fu, "Generative adversarial networks for detecting contamination events in water distribution systems using multi-parameter, multi-site water quality monitoring," *Environmental Science and Ecotechnology*, vol. 14, Apr. 2023, doi: 10.1016/j.ese.2022.100231.
- [85] B. Yilmaz and R. Korn, "Synthetic demand data generation for individual electricity consumers: Generative Adversarial Networks (GANs)," Energy and AI, vol. 9, Aug. 2022, doi: 10.1016/j.egyai.2022.100161.
- [86] Z. Chen, Z. Zeng, H. Shen, X. Zheng, P. Dai, and P. Ouyang, "DN-GAN: Denoising generative adversarial networks for speckle noise reduction in optical coherence tomography images," *Biomed Signal Process Control*, vol. 55, Jan. 2020, doi: 10.1016/j.bspc.2019.101632.
- [87] J. Jiang, G. Li, S. Wu, H. Zhang, and Y. Nie, "BPA-GAN: Human motion transfer using body-part-aware generative adversarial networks," *Graph Models*, vol. 115, May 2021, doi: 10.1016/j.gmod.2021.101107.
- [88] Y. Xiao, W. Lei, L. Lu, X. Chang, X. Zheng, and X. Chen, "CS-GAN: Cross-Structure Generative Adversarial Networks for Chinese calligraphy translation[Formula presented]," *Knowl Based Syst*, vol. 229, Oct. 2021, doi: 10.1016/j.knosys.2021.107334.
- [89] D. M. Vo, D. M. Nguyen, T. P. Le, and S. W. Lee, "HI-GAN: A hierarchical generative adversarial network for blind denoising of real photographs," Inf Sci (N Y), vol. 570, pp. 225–240, Sep. 2021, doi: 10.1016/j.ins.2021.04.045.
- [90] A. R. Pathak, M. Pandey, and S. Rautaray, "Application of Deep Learning for Object Detection," in *Procedia Computer Science*, Elsevier B.V., 2018, pp. 1706–1717. doi: 10.1016/j.procs.2018.05.144.
- [91] A. Garcia-Garcia, S. Orts-Escolano, S. Oprea, V. Villena-Martinez, P. Martinez-Gonzalez, and J. Garcia-Rodriguez, "A survey on deep learning techniques for image and video semantic segmentation," *Applied Soft Computing Journal*, vol. 70. Elsevier Ltd, pp. 41–65, Sep. 01, 2018. doi: 10.1016/j.asoc.2018.05.018.
- [92] S. W. Lee *et al.*, "Towards secure intrusion detection systems using deep learning techniques: Comprehensive analysis and review," *Journal of Network and Computer Applications*, vol. 187. Academic Press, Aug. 01, 2021. doi: 10.1016/j.jnca.2021.103111.
- [93] W. Han, R. Feng, L. Wang, and Y. Cheng, "A semi-supervised generative framework with deep learning features for high-resolution remote sensing image scene classification," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 145, pp. 23–43, Nov. 2018, doi: 10.1016/j.isprsjprs.2017.11.004.

- [94] A. S. Gaafar, J. M. Dahr, and A. K. Hamoud, "Comparative Analysis of Performance of Deep Learning Classification Approach based on LSTM-RNN for Textual and Image Datasets," *Informatica (Slovenia)*, vol. 46, no. 5, pp. 21–28, 2022, doi: 10.31449/inf.v46i5.3872.
- [95] N. H. Ajam and Z. S. Jumaa, "Convolutional neural network in the classification of COVID-19," Original Research, vol. 10, no. 2, pp. 241–250, 2022.
- [96] W. L. Alyoubi, W. M. Shalash, and M. F. Abulkhair, "Diabetic retinopathy detection through deep learning techniques: A review," *Informatics in Medicine Unlocked*, vol. 20. Elsevier Ltd, Jan. 01, 2020. doi: 10.1016/j.imu.2020.100377.
- [97] H. Jindal, N. Sardana, and R. Mehta, "Analyzing Performance of Deep Learning Techniques for Web Navigation Prediction," in *Procedia Computer Science*, Elsevier B.V., 2020, pp. 1739–1748. doi: 10.1016/j.procs.2020.03.384.
- [98] I. Singh, G. Goyal, and A. Chandel, "AlexNet architecture based convolutional neural network for toxic comments classification," Journal of King Saud University - Computer and Information Sciences, vol. 34, no. 9, pp. 7547–7558, Oct. 2022, doi: 10.1016/j.jksuci.2022.06.007.
- [99] C. Chen, Y. Liu, M. Kumar, and J. Qin, "Energy Consumption Modelling Using Deep Learning Technique A Case Study of EAF," in *Procedia CIRP*, Elsevier B.V., 2018, pp. 1063–1068. doi: 10.1016/j.procir.2018.03.095.
- [100] H. Hakim, Z. Alhakeem, and S. Al-Darraji, "Goal location prediction based on deep learning using rgb-d camera," Bulletin of Electrical Engineering and Informatics, vol. 10, no. 5, pp. 2811–2820, Oct. 2021, doi: 10.11591/eei.v10i5.3170.
- [101] H. Jindal, N. Sardana, and R. Mehta, "Analyzing Performance of Deep Learning Techniques for Web Navigation Prediction," in *Procedia Computer Science*, Elsevier B.V., 2020, pp. 1739–1748. doi: 10.1016/j.procs.2020.03.384.
- [102] I. AbdulNabi and Q. Yaseen, "Spam email detection using deep learning techniques," in Procedia Computer Science, Elsevier B.V., 2021, pp. 853–858. doi: 10.1016/j.procs.2021.03.107.
- [103] L. S. Nair, M. K. Shivani, and S. Jo Cheriyan, "Enabling Remote School Education using Knowledge Graphs and Deep Learning Techniques," Procedia Comput Sci, vol. 215, pp. 618–625, 2022, doi: 10.1016/j.procs.2022.12.064.
- [104] M., Buyukyilmaz and A. O. & Cibikdiken, "Voice gender recognition using deep learning," *Methods Ecol Evol*, vol. 2016, December, no. 2, pp. 409–411, Feb. 2016, doi: 10.1111/2041-210X.12624.
- [105] I. Z., Mukti and D. & Biswas, "Transfer learning based plant diseases detection using ResNet50," International conference on electrical information and communication technology (EICT), vol. 2019, December, p. (pp. 1-6), 2019.
- [106] M. Ahmed, N. Afreen, M. Ahmed, M. Sameer, and J. Ahamed, "An inception V3 approach for malware classification using machine learning and transfer learning," *International Journal of Intelligent Networks*, vol. 4, pp. 11–18, Jan. 2023, doi: 10.1016/j.ijin.2022.11.005.
- [107] J. Guérin, S. Thiery, E. Nyiri, O. Gibaru, and B. Boots, "Combining pretrained CNN feature extractors to enhance clustering of complex natural images," *Neurocomputing*, vol. 423, pp. 551–571, Jan. 2021, doi: 10.1016/j.neucom.2020.10.068.
- [108] M. A. Benallal and M. S. Tayeb, "An image-based convolutional neural network system for road defects detection," IAES International Journal of Artificial Intelligence, vol. 12, no. 2, pp. 577–584, Jun. 2023, doi: 10.11591/ijai.v12.i2.pp577-584.
- [109] M. R. Sanzana, T. Maul, J. Y. Wong, M. O. M. Abdulrazic, and C. C. Yip, "Application of deep learning in facility management and maintenance for heating, ventilation, and air conditioning," *Automation in Construction*, vol. 141. Elsevier B.V., Sep. 01, 2022. doi: 10.1016/j.autcon.2022.104445.
- [110] A. Narayan and P. H. O'N Roe, "Learning Graph Dynamics using Deep Neural Networks," Elsevier B.V., Jan. 2018, pp. 433–438. doi: 10.1016/j.ifacol.2018.03.074.