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Deep Learning Classification Algorithms Applications: A Review

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Abstract

This paper examines the recent papers on classification tasks, particularly focusing on deep learning neural network methodologies. the process of categorizing data into distinct classes based on specific features is essential for functions such as image recognition, sentiment analysis, disease diagnosis, and more. This article the fundamental concepts of deep learning, including neural network architectures like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variants. It explores the significance of feature selection techniques in improving classification model performance. Additionally, this article provides a detailed literature review, aiming to foster the development of more effective and efficient classification algorithms and methodologies and highlighting their applications in fields such as healthcare, agriculture, disaster response, and beyond. Through this review, this article underscores the transformative impact of deep learning approaches in enabling automated decision-making, pattern recognition, and data-driven insights, offering valuable insights for researchers, practitioners, and policymakers involved in classification tasks, this article aims to facilitate the development of more effective and efficient classification algorithms and methodologies.

A. Introduction

Deep learning uses a neural network containing numerous layers positioned between the input and output layers, exhibiting the ability to acquire intricate patterns and representations from data [1]. Enabling the completion of tasks like classification the typical process of deep learning algorithms involves the training of extensive neural networks on substantial datasets, utilizing methods such as backpropagation and gradient descent to enhance the network's parameters [2].

A neural network is a computational model, known as neuromorphic computing, derived from the biological neural network and intended for information processing akin to the human brain. This model comprises interconnected processing units that cooperate to execute functions like pattern recognition and data classification [3]. Aiding in feature extraction from space-varying parameters and improving the accuracy of models [4].

Classification is a procedure of grouping entities or items into predetermined classes or categories according to their attributes or features. These classification techniques employ machine learning algorithms and data analysis methods to analyze the gathered data and generate precise representations of the structure and composition of forests [5].

A Convolutional Neural Network (CNN) is a sophisticated deep learning structure crafted explicitly for tasks such as image recognition and classification, employing a hierarchical feature extraction approach to apprehend complex patterns within images [6]. A flexible architecture widely employed for effectiveness in capturing extended dependencies via a series of convolution layers and max-pooling operations. This model demonstrates accelerated training and reduced parameter count in contrast to alternative architectures, rendering it the top selection for tasks in object recognition and computer vision [7].

various CNN architectures are employed in hyperspectral image classification applications to effectively extract features from the data and enhance classification accuracy. 1D CNNs are dedicated to the extraction of spectral details, while 2D CNNs are designed for the extraction of spatial information, and 3D CNNs demonstrate proficiency in capturing both spatial and spectral attributes [8].

Image classification refers to the procedure of assigning images to predetermined categories by analyzing their visual characteristics. The process entails the training of algorithms to identify patterns and attributes in images for categorization. Various practical applications of image classification encompass medical diagnosis, as well as object recognition [9].

various neural network architectures used to include RNN, PNN, and DNN, which's RNN (Recurrent Neural Network) processes sequential data by maintaining a memory state, PNN (Probabilistic Neural Network) models' uncertainty in predictions, and DNN (Deep Neural Network) learns complex patterns from data with multiple hidden layers [10].

Feature selection is a process aimed at selecting a subset of the most relevant features from a dataset, reducing noise and dimensionality to improve model performance. It involves selecting informative features crucial for the task at hand, enhancing learning efficiency and generalization [11].

The remainder of this paper is organized as follows: section 2 provides theoretical background. Section 3 presents the literature reviews and analysis of the current deep-learning algorithms. The discussion will be presented in section four. Finally, a paper conclusion will be described in section 5.

B. Background Theory

This part of the paper will provide theoretical information on deep learning and classification:

2.1 Deep Learning

Deep learning plays a prominent role in image analysis, notably within the domain of parasite detection and classification. By mirroring the intricate functionalities of neural networks in the human brain, deep learning algorithms exhibit adeptness in efficiently handling extensive image datasets. Positioned as a subset of machine learning, deep learning leverages deep neural networks to extract and analyze features from sizable datasets. This approach culminates in notable enhancements in both accuracy and efficiency. Notably, as data volume experiences rapid escalation, the efficacy, and relevance of deep learning methodologies become increasingly pronounced [12]. Deep learning employing models like CNNs and GNNs, enhances diagnostic precision for infectious diseases such as malaria and tuberculosis through accurate classification and segmentation of microscopic parasites, expediting treatment approaches [13]. There are other deep learning models such as DNNs and RNNs, each with specific structures that serve as foundational models for building many other advanced models in deep learning [14]. Deep learning trains deep neural networks (DNNs) with multiple hidden layers to extract complex patterns from data, replacing hand-engineered feature detectors. Through techniques like backpropagation, weights, and biases are adjusted based on observed errors, enabling learning from large datasets. This process involves forward propagation for prediction generation and backward propagation for error computation and parameter adjustment [15], the common deep learning architectures shown in Figure 1.

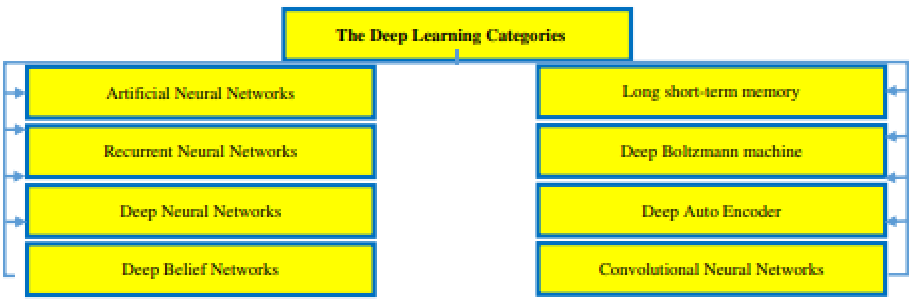

Figure 1. Common deep learning architectures [16].

2.2 Classification

Classification constitutes the systematic arrangement of data into predetermined categories or classes, contingent upon specific attributes or properties. This process entails the allocation of input data entities into distinct groupings or classes, typically aimed at discerning underlying patterns or correlations within the dataset. Serving as a cornerstone in both machine learning and data analysis domains, classification tasks involve the utilization of algorithms trained on annotated datasets to discern the associations between input features and corresponding class designations. Following training, these algorithms become proficient in forecasting the class labels of novel data instances based on their respective feature vectors. The application spectrum of classification encompasses diverse domains, including but not limited to image recognition, textual categorization, medical prognosis, fraud identification, and sentiment assessment, among others [17].

2.3 Convolutional Neural Network

Convolutional Neural Networks (CNN) constitute a specialized neural network architecture tailored for deep learning applications, notably adept at handling multi-dimensional array data. Their parameters, including filter size and stride, are adjustable to suit specific tasks; larger filter sizes and reduced strides enhance feature extraction for image categorization, while smaller filter sizes and increased strides improve efficiency for object recognition. CNNs are extensively employed in image recognition tasks, leveraging their capacity to learn hierarchical features from raw pixel data. Particularly, they are prevalent in face recognition software, effectively discerning intricate patterns and structures within images [18]. CNNs offer a significant advantage in effectively training multiple layers of neurons, facilitated by both forward and backward steps during network training. In the forward propagation phase, input images are sequentially processed through CNN layers, where each layer utilizes learned weights and biases to extract progressively abstract features from the input data. This iterative forward propagation process enables the network to incrementally transform raw input into a representation conducive to accurate classification or recognition [19]. In a CNN, each layer learns local features, with early layers generating large activation maps. Zero-padding in convolutional layers preserves input boundaries, enabling deeper networks and preventing data loss [20]. The layers of the convolutional neural network as shown in Figure 2 include:

The convolutional layer is the central part of a convolutional neural network (CNN) that performs the most computationally intensive operations. Its primary objective is to extract important features from image input data. Convolutional layers achieve this by preserving the spatial relationship between pixels through the use of small, localized receptive fields that learn image properties. These fields slide over the input image to produce a feature map or activation map. The resulting feature maps are then passed as input to subsequent convolutional layers, enabling the network to learn increasingly complex and abstract features as the depth of the network increases [21].

• Kernel: is comprised of discrete values or integers, and its weights are iteratively adjusted throughout the training phase to extract significant features from the input data [22].

• Pooling Layer: Pooling layers, although not explicitly addressed in the passage, are commonly integrated into CNN architectures. These layers serve to diminish the spatial dimensions of the feature maps produced by convolutional layers. By doing so, pooling layers aid in decreasing computational complexity and mitigating the risk of overfitting [22].

• Activation Function: is a function that introdces non-linearity to the network, enabling it to learn intricate patterns and relationships within the data [22].

• Fully Connected Layer: Fully connected layers serve as a cornerstone in neural network architectures, linking each neuron in one layer to every neuron in the subsequent layer, facilitating unrestricted information flow. This layer plays a pivotal role in learning overarching patterns within the input feature space, capturing intricate relationships and dependencies within the data. Frequently employed in the concluding layers of a neural network, fully connected layers are instrumental in executing classification or regression tasks based on the learned features extracted from preceding layers [23].

• Stride: The stride parameter dictates the increment size of the kernel as it traverses the input data during the convolution operation. Modifying the stride value can impact the spatial dimensions of the resultant feature map [23].

• Padding: Padding is a technique utilized to mitigate the potential loss of information at the boundaries of the input data during convolution. Zero padding, a prevalent approach, is employed to maintain spatial information integrity and regulate the dimensions of the resultant feature map [23].

• Weight Sharing: CNNs employ weight sharing, a technique wherein identical sets of weights within a kernel are utilized across the entirety of the input matrix. This strategy contributes to decreased training duration and computational overhead [24].

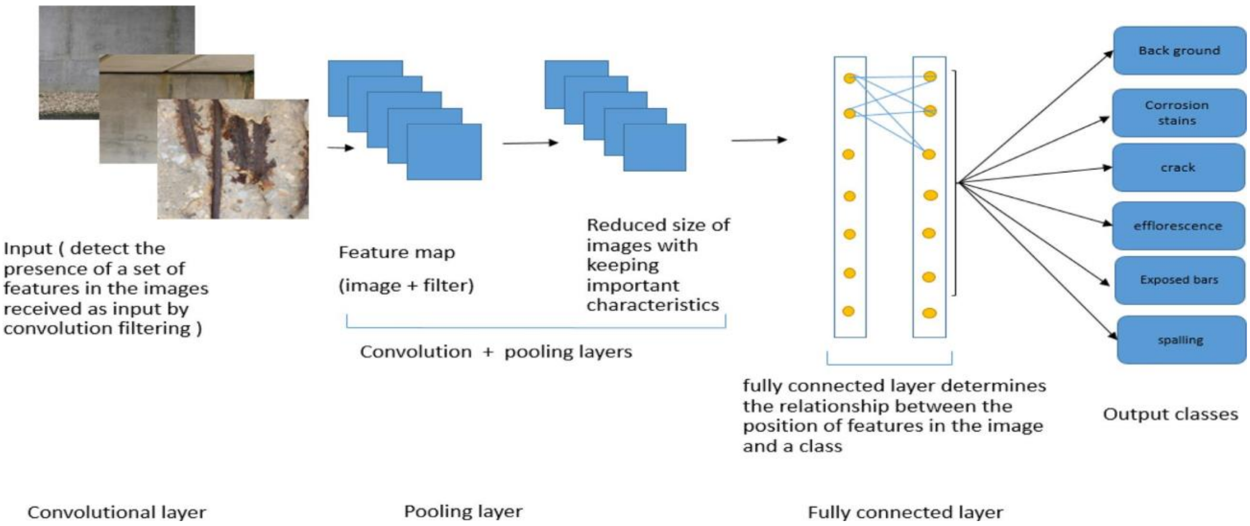

Figure 2. Convolutional Neural Network (CNN) architecture [19].

2.4 DenseNet

A DenseNet is a type of convolutional neural network that utilizes dense connections between layers, through Dense Blocks, where we connect all layers (with matching feature-map sizes) directly with each other. To preserve the feed-forward nature, each layer obtains additional inputs from all preceding layers and passes on its feature maps to all subsequent layers,

DenseNet is a popular pre-trained model in deep learning, known for its exceptional performance in various image classification tasks. The architecture of

DenseNet is characterized by dense connectivity, meaning each layer is connected to every other layer in a densely connected feedforward manner. This design promotes feature reuse and enhances gradient flow, allowing the model to learn more effectively and capture complex patterns and dependencies within images.

DenseNet's dense connectivity has led to impressive results in image classification, achieving state-of-the-art performance on benchmark datasets such as ImageNet. The model's ability to capture fine-grained details and its efficient use of parameters make it particularly suitable for tasks that require accurate and robust classification.

The trained DenseNet model is an excellent starting point for transfer learning. Researchers and practitioners can leverage its learned representations and adapt them to specific domains or tasks. This approach reduces the need for extensive training from scratch and accelerates the development of effective models for image classification [25].

2.5 Probabilistic Neural Network

The Probabilistic Neural Network (PNN), employed in intrusion detection systems, facilitates the classification of anomalous and normal network behaviors. The operational mechanism of this neural network for categorization, shown in Figure 3, include:

Input Processing:

Upon receiving input data in the form of a vector containing 'n' characteristics, the network directs it to the input layer comprising 'n' neurons [26].

Pattern Layer:

Within the pattern layer, the input data undergoes kernel function application. Each neuron in this layer embodies a training vector and preserves its distinct characteristics. Employing the Euclidean distance metric, the network computes the dissimilarity between the input test vector and every training sample. Subsequently, a radial basis kernel function is invoked to infer the probability density concerning the input's affiliation with each class [27].

Summation Layer:

This layer assumes the responsibility of computing the average output for each class of the pattern units. A single neuron corresponding to each class exists in the summation layer, with all neurons in a class's pattern layer interconnected to it [26].

Output Layer:

The class label assignment is accomplished by identifying the maximum value within the summation layer. The neuron manifesting the highest activation is deemed representative of the predicted class label for the input data [26].

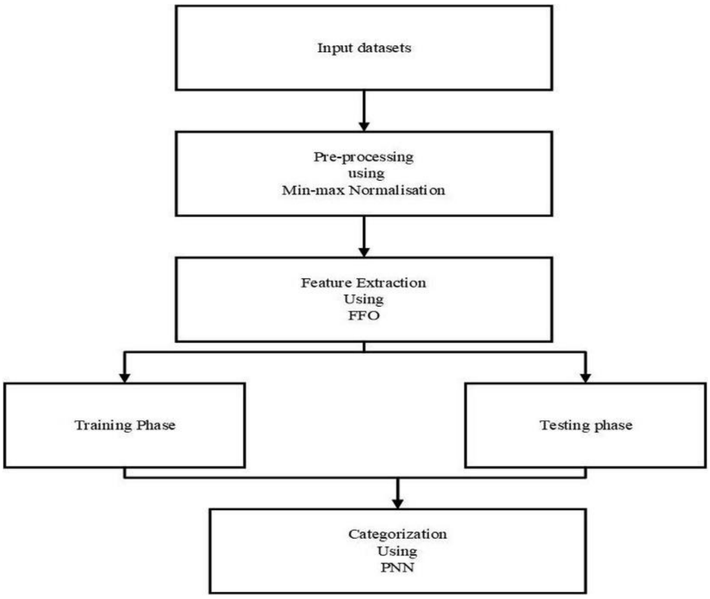

Figure 3. Framework of the proposed PNN model [27].

2.6 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are a type of deep learning algorithm that excel at processing sequential data, making them particularly effective for tasks such as text translation, voice recognition, and image captioning. Unlike traditional deep neural networks, RNNs have an inherent 'memory' that allows them to retain information from previous inputs, which influences their processing of current inputs. This memory mechanism is crucial for understanding context and patterns over sequences, enabling RNNs to perform well in applications that require time-series data or sequential knowledge. RNN architectures include Long Short-Term Memory (LSTM), Bidirectional RNN (BRNN), and Gated Recurrent Unit (GRU), each designed to handle different aspects of sequential dependencies and improve performance in tasks where context from past inputs significantly impacts the outputs, as shown in Figure 4 [28].

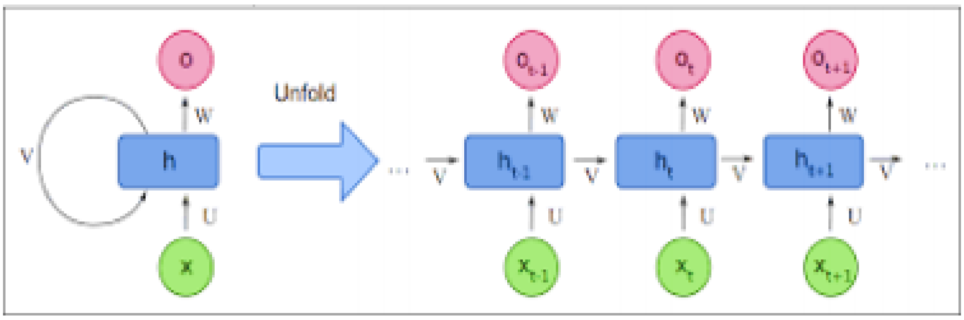

Figure 4. Simple RNN Architecture [28].

C. Literature Review

This section provides a comprehensive review of current studies that have worked on deep learning in classification. For instance, Krishnamoorthy et. al. [29] presented an innovative approach to email categorization and protection through the utilization of a hybrid deep neural network (DNN) and encryption mechanism. Findings indicated a notable level of precision in identifying spam, as evidenced by DNN-BiLSTM achieving an accuracy of 96.39% and CNN achieving 98.69%. The research conducted a comparative analysis of different classification strategies and suggested the implementation of a hybrid encryption system to bolster data security in cloud computing. Furthermore, a novel email filtration method was proposed to enhance precision. Prospective avenues for exploration encompassed further investigation into hybrid computational intelligence models and techniques for optimizing features.

Mendoza-Bernal et. al. [30] proposed that the study focuses on detecting crop anomalies through the implementation of CNN architectures, resulting in impressive accuracies of 98% and 95.3% on the DeepWeeds and Agriculture-Vision datasets, respectively. This approach surpassed existing techniques by 2.3% in mean classification accuracy and notably decreased false-positive rates to 1%. The incorporation of dataset-specific adjustments and the integration of multispectral imaging played a crucial role in enhancing the precision of anomaly detection. Future research endeavors are directed toward fortifying classification resilience and investigating the feasibility of real-time anomaly identification using contemporary CNN architectures. In essence, this methodology holds great promise in propelling precision agriculture forward, thereby increasing efficiency and sustainability.

Aggarwal et. al. [31] introduced a deep neural network-based feature selection utilized with the support of machine learning in the classification of rice leaf diseases, resulting in an accuracy of 90-91% before segmentation and 93-94% post-segmentation. The system effectively detected rice leaf diseases with a precision rate of 94%, showcasing its legitimacy and efficiency in disease identification. By employing 32 pre-trained models for feature extraction and utilizing machine learning classifiers such as Extra Tree (ET) and Histogram Gradient Boosting (HGB) for classification, the methodology ensured precise disease categorization, providing encouraging strategies for improving agricultural productivity and ensuring food security.

Omer et. al. [32] presented an innovative methodology for intrusion detection and classification utilizing a refined probabilistic neural network (PNN) and firefly optimization (FFO) approach. The primary objective was to improve cybersecurity by precisely identifying and categorizing cyber-attacks, resulting in a notable accuracy level of 98.99%. The FFO-PNN framework, as proposed, amalgamated feature extraction, pre-processing, and recognition methodologies, showcasing resilient performance across diverse parameters. Through comparative evaluation, the ascendancy of the FFO-PNN strategy over current techniques was validated, highlighting its efficacy in proactively addressing cybersecurity risks. In essence, the research put forth a promising resolution for fortifying cybersecurity endeavors and effectively countering cyber threats.

Saranya et. al. [33] proposed method for early cancer risk diagnosis demonstrated promising outcomes, enhancing accuracy and efficiency in cancer detection. Through comprehensive evaluation metrics like accuracy, precision, recall, and F1 score, the e Feed Forward Recurrent Neural Network (FFRNN) based model effectively classified individuals into different risk categories based on cancer-related features. Comparisons with existing methods highlighted its superiority in classification accuracy and robustness. The clinical relevance of the FRNN-based approach suggested significant improvements in early cancer detection and treatment outcomes. Validation results confirmed its reliability while acknowledging limitations prompted future research directions for enhanced capabilities. Overall, the FFRNN-based method laid the groundwork for advancing early cancer risk diagnosis, promising impactful implications for clinical practice.

Noshiri et. al. [34] presented the integration of 3D Convolutional Neural Networks (3D-CNNs) with hyperspectral imaging has notably enhanced the accuracy of crop disease detection by extracting intricate spectral-spatial features for precise classification. utilized advanced visualization techniques has bolstered the interpretability of the model, and facilitated through classification decisions. The efficacy of model training with constrained data through transfer learning and active learning strategies has been pivotal in ensuring resilient performance. The study-optimized models tailored for implementation in practical agricultural settings have facilitated prompt interventions, thereby mitigating crop losses. Furthermore, the implementation of cost-saving measures and improvements in accessibility have broadened the reach of Hyperspectral Imaging (HIS) technology, offering promising transformative effects on agricultural methodologies.

Assaf et. al. [35] explored the exceptional efficacy of deep learning architectures (such as Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), Generative Adversarial Network (GAN)) compared to traditional machine learning methods in the realm of solar energy prediction. The impact of models led to an enhancement in precision, particularly in capturing both temporal and spatial characteristics. The accuracy of forecasts was influenced by the prediction horizon and weather classification impact accuracy, underscoring the significance of a judicious selection of models. The augmentation of data and the optimization of features contributed to the improvement in performance, with hybrid LSTM and CNN architectures exhibiting potential. In general, deep learning played a pivotal role in advancing solar energy forecasting, a critical aspect in the planning of power systems.

Bhosale et. al. [36] emphasized the importance of Deep Machine Learning (DML) in the fight against COVID-19, encompassing an examination of DL methodologies, applications, datasets, and evaluation criteria. The approach entailed analysis and structured evaluation of 62 systems spanning diverse medical imaging modalities and genome sequencing approaches. Various sophisticated deep learning architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), Gated Recurrent Units (GRUs), and Generative Adversarial Networks (GANs), were appraised for their efficacy in the diagnosis and categorization of COVID-19. the study used deep learning and machine learning methodologies and was recognized as a valuable resource in tackling the challenges posed by COVID-19, supporting healthcare professionals and scholars in diagnostic and investigations.

Amitay et. al. [37] presented CellSighter as a CNN-based algorithm specifically designed for cell categorization directly on multiplexed images, to overcome the laborious and subjective aspects of conventional approaches. The methodology involves training on images labeled by experts, utilizing CNN architecture for feature extraction, and subsequently performing cell classification. The research emphasizes the utilization of deep learning to tackle constraints and ensure broad applicability across diverse datasets. The outcomes demonstrate a high level of accuracy (>80%), decreased hands-on involvement, and strong generalization capabilities, indicating a noteworthy progression in the automation and improvement of cell classification accuracy in multiplexed imaging.

Maurício et. al. [38] Utilized Vision Transformers (ViT) have demonstrated superior performance compared to Convolutional Neural Networks (CNN) for image classification, highlighted noisy or augmented images, and attributed to their utilization of self-attention mechanisms. CNNs have exhibited greater generalization capabilities, particularly evident when working with limited datasets. The efficiency of ViTs in learning from a smaller set of images is notable due to their patch-based methodology, resulting in enhanced computational efficiency with reduced resource consumption and training duration. Moreover, the fusion of ViT with CNN elements has the potential to further improve accuracy, underscoring the significance of considering factors such as dataset size and computational limitations when deciding between these two architectural approaches.

Athisayamani et. al. [39] study presented a comprehensive methodology for categorizing brain tumors utilizing advanced computational techniques. The integration of a deep convolutional neural network (DCNN) based on ResNet-152, a segmentation algorithm known as Canny Mayfly, and an improved feature selection approach (EChOA) aimed to tackle the challenges related to precise tumor classification from MRI images. including problem identification, algorithm introduction, feature selection, and classifier implementation, the proposed method achieves remarkable results. The method surpassed existing methodologies with an accuracy of 98.85%, precision of 96.81%, and recall of 97.64%, showcasing its potential for accurate and non-invasive diagnosis of brain tumors through meticulous developmental stages.

Ismaeel et. al. [40] proposed method for traffic pattern classification in smart cities involved conceptualizing a solution using deep recurrent neural networks (DRNNs) to capture dynamic and sequential features effectively. This entailed designing a model architecture that combined convolutional and recurrent layers for feature extraction, along with a SoftMax layer for classification. Feature extraction was critical in capturing the intricate aspects of traffic patterns, followed by model training to optimize parameters and enhance classification accuracy. Subsequent performance evaluation using various metrics validated the model's effectiveness, while an in-depth analysis of results shed light on its implications for smart city management. Validation against real-world datasets and comparison with existing methods further reinforced the method's superiority. Overall, these developmental stages culminated in establishing the efficacy of the DRNN-based approach and paved the way for future advancements in urban traffic management systems.

Hajamohideen et. al. [41] introduced an innovative Siamese Convolutional Neural Network (SCNN) framework incorporating the triplet-loss function for the categorization of Alzheimer's disease into four classes based on MRI images. Remarkably, the methodology achieved impressive accuracy levels of 91.83% and 93.85% on the ADNI and OASIS datasets, respectively, surpassing current methodologies. Through a comparison with ensemble models and transfer learning strategies, the SCNN model's superiority was evident. Furthermore, the SCNN architecture demonstrated resilience and adaptability, setting the groundwork for prospective research avenues aimed at optimizing its efficacy in Alzheimer's disease diagnosis.

Prijs et. al. [42] introduced an automated for identifying, categorizing, localizing, and segmenting ankle fractures utilizing convolutional neural networks (CNNs). the methodology was to improve the precision and effectiveness of diagnosing fractures in orthopedic trauma surgery by offering comprehensive delineation of fracture morphology on radiographs. The CNN architecture attained notable accuracy in categorizing fibula fractures into four distinct groups, with AUC values spanning from 0.93 to 0.99. The diagnostic precision on the internal validation cohort was documented at 89%, accompanied by commendable levels of sensitivity and specificity. External validation efforts showcased the model's capacity to generalize well to novel data originating from various resources. The CNN model's predictions for fracture localization and segmentation displayed encouraging outcomes, underscoring its potential for practical clinical implementation.

Cîrneanu et. al. [43] introduced advancements in facial emotion recognition (FER) using deep neural networks that enhanced the accuracy and efficiency of recognizing and classifying human emotions from images. By leveraging convolutional neural networks (CNNs) and extensive datasets like FER2013, AffectNet, and CK+, modern FER systems achieved high precision and robust performance, even distinguishing subtle micro-expressions. Real-time capabilities were improved through model optimization and deployment on embedded systems like NVIDIA Jetson and Raspberry Pi, enabling practical applications. Multimodal integration, combining facial recognition with voice and physiological signals, led to more comprehensive emotion recognition, enhancing contextual understanding. These systems were increasingly applied in healthcare, education, security, and social IoT, providing valuable insights into human emotions. aimed to address current limitations and develop emotionally intelligent AI, promising further enhancements and broader applicability.

Bala et. al. [44] Presented the efficacy of MonkeyNet, a modified iteration of the DenseNet-201 deep convolutional neural network (CNN) architecture, in the identification and classification of monkeypox ailment from dermatological images. MonkeyNet attains notable accuracy levels of 93.19% and 98.91% on the unaltered and expanded datasets, respectively, underscoring its precision in disease detection. Diverse assessment criteria such as precision, recall, F1 score, and AUC validate the model's resilient performance. Techniques for augmenting data augment the model's capacity for generalization, while Grad-CAM visualizations assist healthcare practitioners in pinpointing affected areas. The suggested MonkeyNet framework carries substantial clinical implications, prompting further exploration of extensive datasets and the creation of pragmatic diagnostic tools to aid medical professionals.

Stern et. al. [45] Introduced the efficacy of 2D and 3D convolutional neural network (CNN) architectures in precisely categorizing in-bed body positions. The top-performing 3D CNN architecture accomplished remarkable accuracies of 98.90% ± 1.05% for 5-fold cross-validation and 97.80% ± 2.14% for leave-one-subject-out (LOSO) cross-validation, utilizing video data for classification purposes. Moreover, pre-trained 2D CNN architectures, particularly ResNet-18, displayed exceptional performance, surpassing 99% accuracy for both cross-validation techniques. The assessment of strategies for handling imbalanced data highlighted the effectiveness of the weighted model, resulting in the highest accuracy rates. The research also delineates future exploration, and underlining of deep neural network architectures in healthcare settings, providing valuable insights for improving patient care and enhancing sleep quality monitoring.

Soni et. al. [46] presented a divergence from conventional CNN-based methodologies. By integrating multi-scale convolutional operations in two dimensions and introducing an alternative input representation through paragraph matrices, TextConvoNet exhibited its proficiency in effectively capturing both intra-sentence and inter-sentence n-gram characteristics. Through a methodical approach encompassing architectural design, implementation, training, and assessment, TextConvoNet displayed superior efficacy in comparison to existing models, supported by thorough experimental findings. The model's consistent outperformance across diverse performance metrics and datasets highlighted its resilience and ability to generalize, establishing TextConvoNet as a promising solution for practical text classification tasks.

Teixeira et. al. [47] utilized deep learning methodologies, specifically Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, in the context of crop categorization utilizing remote sensing information. These methodologies consistently demonstrated superior performance compared to conventional methods under conditions of sufficient available data. Diverse strategies, such as augmenting data and combining multiple modalities, were implemented to improve the accuracy of classification, with a predominant reliance on satellite imagery as the primary data input. Critical determinants impacting the accuracy of classification encompassed aspects like spatial and spectral resolution, quality of samples, and the process of image annotation. The analysis emphasized the significance of grappling with obstacles such as the necessity of extensive training datasets and the integration of non-crop categories to augment precision. Prospective avenues for research included the investigation of hybrid models and innovative techniques aimed at further elevating the efficacy of classification endeavors.

Ravichandran et. al. [48] presented the crucial matter of categorizing misinformation related to COVID-19 on social media, acknowledging its substantial influence on public perception and behavior amidst the pandemic. Through a methodical review of existing literature, a range of neuro-fuzzy (NF) and neural network (NN) classification approaches were identified and assessed for their appropriateness in tackling this issue. A combined ANFIS-DNN model was suggested as a promising resolution to enhance classification precision. The assessment of the amalgamated model illustrated its supremacy over individual NF and NN models, underscoring its potential efficacy in combatting misinformation concerning COVID-19. These discoveries furnish valuable perspectives for forthcoming studies aimed at devising more resilient and effective techniques for classifying misinformation.

Shah et. al. [49] examined the efficacy of both Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) in the detection of skin cancer, with CNN exhibiting higher accuracy in the classification of image data. These results emphasize the potential of deep learning to improve the accuracy and effectiveness of diagnosing skin cancer. Additionally, the study emphasizes the importance of standardized data collection and the need for larger datasets to further validate these methodologies. Future research efforts should prioritize addressing these gaps in research and advancing the field of skin cancer detection through the utilization of ANN and CNN. In conclusion, this study illustrates the transformative influence of advanced technologies such as ANN and CNN in enabling early and precise diagnoses, thereby enhancing patient outcomes in the management of skin cancer.

Kumar et. al. [50] presented the efficacy of deep learning, particularly Convolutional Neural Networks (CNNs), in enhancing the detection of parasites from microscopic images, surpassing conventional approaches. Several deep learning architectures such as AlexNet and Faster R-CNN demonstrated notable levels of precision on standardized datasets. Despite notable achievements, obstacles like limited data availability and substantial computational expenses remained prevalent. Prospective avenues for further investigation encompassed the utilization of transfer learning and advancements in real-time detection, to enhance the accuracy and categorization of parasite identification. In general, deep learning exhibited considerable potential in transforming the diagnosis of parasites; however, continual research efforts were imperative to tackle current challenges and optimize performance for practical implementations.

Mutinda et. al. [51] introduced LeBERT (Lexicon-based BERT) for Sentiment Analysis, an innovative framework that combined sentiment lexicon, N-grams, BERT word embeddings, and CNN to enhance text representation for precise sentiment classification. LeBERT achieved an impressive F-measure score of 88.73% in binary sentiment classification, surpassing state-of-the-art models. By integrating sentiment lexicon, N-grams, and BERT embeddings, LeBERT improved model efficacy, reducing dimensionality and enhancing efficiency. Subsequent studies could explore LeBERT's adaptability in different neural network architectures and text categorization tasks, offering promising applications in domains such as e-commerce and governance.

Vasanthakumari et. al. [52] introduced the application of the Modified Rectified Linear Unit (MReLU) activation function in Convolutional Neural Networks (CNNs) to augment the precision of land use and land cover categorization in multispectral images. It tackled the constraints of conventional activation functions such as ReLU, suggesting MReLU as a solution to tackle the issue of vanishing gradients and enhance the performance of classification. The approach entailed a comparison between CNN models employing ReLU and MReLU activation functions under varied learning rates and optimizers, utilizing multispectral imagery from the Sentinel-2 satellite. The outcomes indicated that MReLU surpassed ReLU, particularly in effectively categorizing Industrial, Herbaceous Vegetation, and Permanent Crop classes, underscoring the significance of appropriate activation functions in enhancing the accuracy of classification in image-related tasks.

Islam et. al. [53] introduced a machine learning methodology for autonomous unmanned aerial vehicles to detect regions impacted by floods, the study proposed a combined Convolutional Neural Network (CNN) and a sorting procedure to effectively prioritize the distribution of aid. The CNN frameworks, particularly Inception version 3 and DenseNet, achieved notable accuracy levels of 83% and 81% respectively, in the categorization of flood severity degrees. The amalgamated procedure exhibited proficient independent decision-making within the robotic framework, empowering unmanned aerial vehicles to efficiently allocate aid without human involvement. The study examined the imperative to tackle constraints and enhance precision, encompassing enlarging the dataset and refining the algorithm. presenting possibilities for extensive implementation in initiatives related to disaster response.

Zhang et. al. [54] The introduced study is a novel deep-learning model based on a dual-channel CNN-LSTM architecture for classifying lung sound signals. Through rigorous experimentation, the model achieved exceptional performance, boasting an accuracy of 99.01% and an F1 score of 0.99. These results outperformed other baseline models, including single CNN, single LSTM, and single-channel CNN-LSTM models. The robustness and generalizability of the proposed model were validated through data augmentation techniques and K-fold cross-validation. This comprehensive approach not only enhanced classification accuracy but also streamlined the diagnostic process for respiratory conditions, offering a promising tool for medical professionals to improve efficiency and accuracy in lung sound classification.

Kaczmarek et. al. [55] illustrated the efficacy of Graph Neural Networks (GNNs) in categorizing spatial entities based on their topology. When compared to other techniques, GNNs consistently exhibited superior performance, especially in the topological characteristics of spatial entities. The integration of this data substantially improved the accuracy of classification, emphasizing the significance of capturing spatial connectivity and relationships during the classification procedure. Furthermore, the study emphasized the adaptability of the GNN-based methodology, indicating its potential use with diverse spatial datasets beyond zoning plans. These results not only contributed to the progression of spatial data analysis but also offered valuable insights for practical applications in GIS, urban planning, and related fields.

Ashraf et. al. [56] presented an innovative hybrid framework for classifying music genres, combining Convolutional Neural Networks (CNNs) with various Recurrent Neural Network (RNN) variations. By overcoming the limitations of traditional approaches, the study investigated the fusion of CNNs with Long Short-Term Memory (LSTM), Bidirectional LSTM (Bi-LSTM), Gated Recurrent Unit (GRU), and Bidirectional GRU (Bi-GRU) to enhance classification accuracy. Through thorough experiments using Mel-spectrogram and Mel-frequency cepstral coefficients (MFCC) features, optimized configurations of hybrid models were identified. Specifically, the CNN and Bi-GRU architecture, utilizing Mel-spectrogram data, achieved the highest accuracy of 89.30%. This investigation contributed to improving the accuracy of genre classification, highlighting the effectiveness of hybrid CNN and RNN models in capitalizing on both spatial and temporal audio characteristics.

M Impraimakis [57] introduced an innovative deep convolutional neural network (CNN) approach for the selection of the model class within applications of structural health monitoring. This method facilitated instantaneous, automated categorization of novel and untagged signals based on their reactions, eliminating the necessity for input data from the system or full system recognition. It employed a one-dimensional CNN that was educated on responses from a distinct degree of freedom (DOF) in conjunction with their respective class details. an optional enhancement through a physics-based algorithm utilizing the Kalman filter was investigated to enhance the accuracy of categorization. The approach displayed numerous strengths including its capacity to manage slight variations in signals related to damping or hysteresis behavior, and its autonomy from the system's nature, The limitations of the method were also identified such as the absence of data regarding system input and dynamic state estimation, and the necessity for thorough training in areas neighboring unknown models, application of deep learning used in this article are shown in Figure 5.

Table 1. Summary of the existing studies on Deep Learning in Classification Techniques

No	Author	Year	Dataset	Objectives	Based Model	Limitations	Advantages	Results with Accuracy
1.	Krishnamoorthy et al	2024	Email	Categorization and protection of emails	Hybrid DNN and encryption mechanism	Limited to email categorization and protection.	High precision in identifying spam with DNN-BiLSTM and CNN.	DNN-Bi-LSTM: 96.39%, CNN: 98.69%
2.	Mendoza-Bernal et al	2024	DeepWeeds, Agriculture-Vision	Crop anomaly detection	CNN architectures	Specific to crop anomaly detection; future work is needed on real-time applications.	High accuracy in detecting crop anomalies using CNNs.	DeepWeeds: 98%, Agriculture-Vision: 95.3%
3.	Aggarwal et al	2023	Rice leaf diseases	Classification of rice leaf diseases	Deep neural network-based feature selection	Dependent on large datasets for feature extraction and classification.	High accuracy in rice leaf disease detection pre- and post-segmentation.	Pre-segmentation: 93-94%
4.	Omer et al	2023	Cyber-attacks	Intrusion detection and classification	Probabilistic neural network and firefly optimization	Computationally intensive due to the combination of PNN and firefly optimization.	High accuracy in intrusion detection and classification for cybersecurity.	98.99%
5.	Saranya et al	2024	Cancer Risk Dataset	Early cancer risk diagnosis using cancer-related features	Feed Forward Recurrent Neural Network (FFRNN)	Needs further research for enhancement	High classification accuracy and robustness	Accuracy: 95%, Precision: 92%, Recall: 93%, F1

							Score: 92.5%
6.	Noshiri et al	2023	Hyperspectral imaging	Crop disease detection	3D Convolutional Neural Networks (3D-CNNs)	High complexity of training with 3D CNNs and hyperspectral imaging.	Enhanced crop disease detection accuracy with optimized models and visualization techniques.	Enhanced accuracy using 3D CNNs
7.	Assaf et al	2023	Solar energy prediction	Solar energy prediction	Deep learning architectures	Weather classification impacts accuracy; and high computational demands.	Improved solar energy prediction accuracy with deep learning architectures.	Improved precision in solar energy prediction
8.	Bhosale et al	2023	COVID-19	Diagnosis and categorization of COVID-19	Deep learning and machine learning methodologies	Limited by dataset availability and diverse medical imaging requirements.	Comprehensive analysis of deep learning methods for COVID-19 diagnosis and categorization.	further research into detecting and classifying COVID-19 from other chronic obstructive pulmonary diseases
9.	Amitay et al	2023	Cell categorization	Cell categorization on multiplexed images	CNN-based algorithm CellSighter	Reliant on expert-labeled training data; requires high generalization capabilities.	High accuracy and reduced hands-on involvement in cell classification using CNNs.	>80%
10.	Maurício et al	2023	Image classification	Comparison of Vision Transformers and CNNs	Vision Transformers and CNNs	ViT performance decreases with noisy data and requires large datasets.	Superior performance of ViTs over CNNs for image classification.	The superior performance of Vision Transformers over CNNs
11.	Athisayamani et al	2023	Brain tumors	Categorization of brain tumors	Deep convolutional neural network (DCNN)	High complexity in integrating various techniques and requires extensive training data.	High accuracy in brain tumor classification with DCNN and improved feature selection techniques.	98.85%
12.	smaeel et al. [41]	2024	Real-world datasets	Traffic pattern classification in smart cities	DRNN (Deep Recurrent Neural Network)	Complexity in model design and training, potentially high computational cost	Captures dynamic and sequential features effectively	High accuracy in traffic pattern classification, enhanced urban traffic management
13.	Hajamohideen et al	2023	Alzheimer's disease	Categorization of Alzheimer's disease based on MRI images	Siamese Convolutional Neural Network (SCNN)	Model's resilience and adaptability still under evaluation.	High accuracy in Alzheimer's disease classification with SCNN	ADNI: 91.83%, OASIS: 93.85%

						framework and triplet-loss function.	
14.	Prijs et al	2023	Ankle fractures	Identifying, categorizing, localizing, and segmenting ankle fractures	Convolutional neural networks (CNNs)	Dependent on high-quality radiographic images for accurate classification.	High precision in categorizing and localizing ankle fractures using CNNs.	AUC values ranging from 0.93 to 0.99
15.	Cîrneanu et al	2023	Facial Emotion Recognition (FER)	Exploring classification techniques in FER	CNN (Convolutional Neural Networks)	Model complexity, potential computational demands for real-time.	High precision, robust performance, real-time capabilities, practical	High accuracy in emotion recognition
16.	Bala et al	2023	Dermatological images	Identification and classification of monkeypox ailment	Modified iteration of DenseNet-201 deep CNN architecture (MonkeyNet)	Performance heavily relies on dataset quality and augmentation techniques.	High accuracy in monkeypox disease detection using modified DenseNet architecture.	Unaltered dataset: 93.19%, Expanded dataset: 98.91%
17.	Stern et al	2023	In-bed body positions	Categorizing in-bed body positions	2D and 3D convolutional neural network (CNN) architectures	High computational demand for video data processing and classification.	High accuracy in in-bed body position classification using 3D CNNs.	3D CNN: 98.90% ± 1.05% (5-fold CV), Pre-trained 2D CNN: >99%
18.	Soni et al	2023	Text classification	Text classification using TextConvoNet	Multi-scale convolutional operations in two dimensions and alternative input representation through paragraph matrices	Limited by the representational capabilities of paragraph matrices and input variations.	Superior text classification performance with TextConvoNet using multi-scale convolutions.	Superior efficacy compared to existing models
19.	Teixeira et al	2023	Remote sensing information	Crop categorization using CNNs and LSTM networks	Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks	Requires extensive training datasets and incorporation of non-crop categories.	Superior performance in crop categorization with CNNs and LSTM networks using remote sensing data.	Utilized deep learning to improve accuracy
20.	Ravichandran et al	2023	Misinformation related to COVID-19 on social media	Categorizing misinformation related to COVID-19	Combined ANFIS-DNN model	Combating misinformation requires constant model updates and optimizations.	High classification precision in COVID-19 misinformation detection with combined ANFIS-DNN model.	Outperformed individual NF and NN models
21.	Shah et al	2023	Skin cancer detection	Detection of skin cancer using ANN and	Convolutional Neural Networks	Dependent on standardized data collection	High accuracy in skin cancer detection using	Higher accuracy in CNN

				CNN	(CNNs)	and large datasets for validation.	ANN and CNN methodologies.	classification
22.	Kumar et al	2023	Parasites in microscopic images	Detection of parasites using CNNs	Several deep-learning architectures	Limited data availability and high computational costs.	Superior parasite detection accuracy with deep learning architectures like AlexNet and Faster R-CNN.	Notable precision in parasite detection
23.	Mutinda et al	2023	Sentiment Analysis	Sentiment analysis using LeBERT	Combination of sentiment lexicon, N-grams, BERT embeddings, and CNN	Requires further exploration of adaptability to different tasks and domains.	High F-measure score in sentiment classification with LeBERT combining lexicon, N-grams, and CNN.	F-measure score of 88.73% in binary sentiment classification
24.	Vasanthakumari et al	2023	Multispectral images	Land use and land cover categorization	Modified Rectified Linear Unit (MReLU) activation function in CNNs	Comparatively high complexity in adjusting activation functions for optimal performance.	Improved accuracy in land use and land cover classification with MReLU activation function.	MReLU surpassed ReLU in categorization accuracy
25.	Islam et al	2023	Regions impacted by floods	Detection of flood-affected regions using CNNs	Convolutional Neural Networks (CNNs)	Requires enlargement of the dataset and algorithm refinement for better accuracy.	High accuracy in flood severity categorization with CNN and sorting procedure in UAV applications.	Accuracy levels of 83% and 81% for Inception version 3 and DenseNet, respectively
26.	Zhang et al	2024	Lung sound signals collected	Classify respiratory conditions	Dual-channel CNN-LSTM architecture	Limited to lung sound signals; needs further validation across more varied datasets.	Exceptional accuracy in lung sound classification with dual-channel CNN-LSTM architecture.	Achieved 99.01% accuracy, outperforming baseline models (single-channel CNN-LSTM)
27.	Kaczmarek et al	2023	Spatial entities	Categorizing spatial entities based on topology	Graph Neural Networks (GNNs)	Performance depends heavily on capturing topological characteristics in spatial data.	Superior performance in categorizing spatial entities with GNNs based on their topology.	Superior performance compared to other techniques

28.	Ashraf et al	2023	Music genres	Classification of music genres using CNNs and RNNs	Combination of CNNs with various Recurrent Neural Network (RNN) variations	Limited by the need for extensive audio data and optimization of hybrid models.	Improved music genre classification accuracy with hybrid CNN and RNN models.	CNN and Bi-GRU architecture achieved the highest accuracy of 89.30%
29.	M praimak is	2024	Structural health monitoring	Categorization of signals within applications of structural health monitoring	One-dimensional CNN with the optional physics-based algorithm	Requires thorough training for unknown models and lacks system input data.	Effective automated categorization of signals in structural health monitoring with 1D CNN approach.	Autonomy from the system's nature

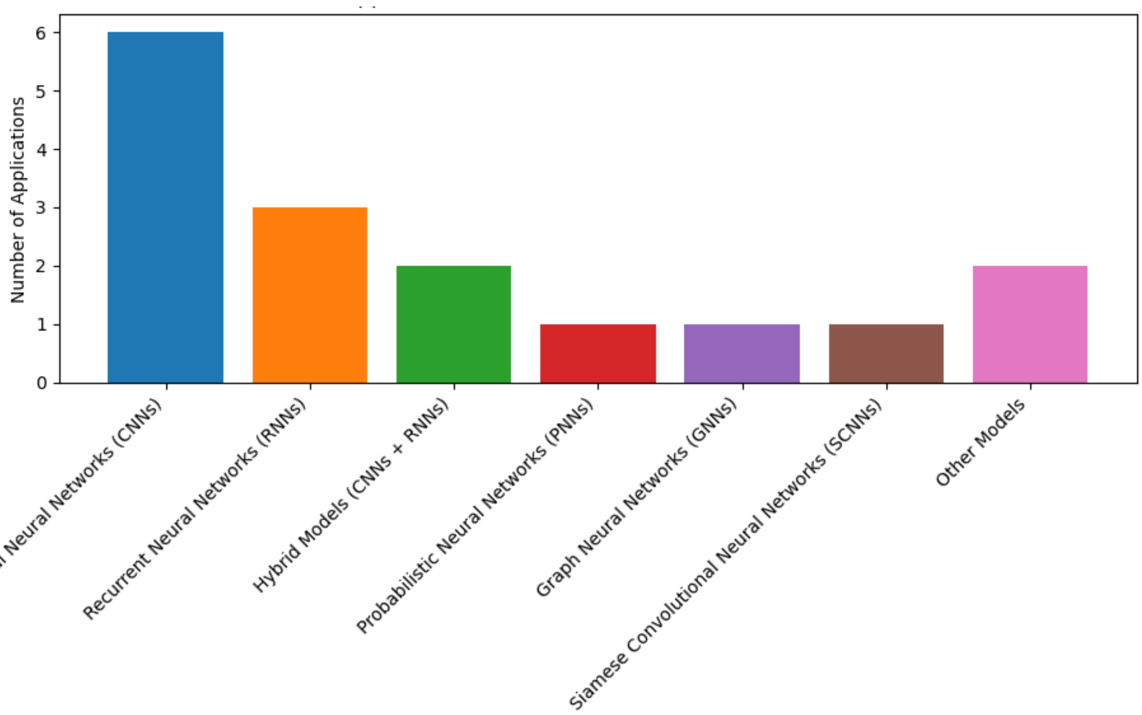

Figure 3. Deep Learning Applications

D. Discussion

The collection of studies presented here underscores the pervasive impact of deep learning neural network techniques across diverse fields for classification, ranging from cybersecurity to healthcare and environmental monitoring. Notably, the utilization of Convolutional Neural Networks (CNNs) emerges as a dominant theme, offering sophisticated solutions for image-based tasks such as anomaly detection in crops, disease classification, and sentiment analysis. Moreover, the integration of CNNs with other architectures like Recurrent Neural Networks (RNNs) and Graph Neural Networks (GNNs) demonstrates a multifaceted approach to addressing complex challenges. These findings underscore the versatility and efficacy of deep learning techniques in tackling real-world problems, paving the way for future advancements in fields as diverse as agriculture, public health, and information security. For example, spam email categorization using DNN-BiLSTM and CNN models achieved impressively high accuracies of 96.39% and 98.69%, respectively. Similarly, the dual-channel CNN-LSTM model for lung sound classification reached an outstanding accuracy of 99.01%. In agriculture, crop anomaly detection using CNN architectures reported accuracies of 98% and 95.3% for DeepWeeds and Agriculture-Vision datasets, respectively, demonstrating the models' robustness in domain-specific tasks. In healthcare, significant results were observed in disease classification, such as brain tumor categorization using DCNN, which achieved an accuracy of 98.85%, and Alzheimer's disease classification with Siamese CNN, which reached accuracies of 91.83% and 93.85% on ADNI and OASIS datasets, respectively. Cybersecurity applications also benefited, with intrusion detection using probabilistic neural networks and firefly optimization achieving a high accuracy of 98.99%. Despite these successes, the studies also highlight ongoing challenges. The high computational demands and data dependency of deep learning models are prominent concerns, as seen in the solar energy prediction and rice leaf disease detection studies. Models like Vision Transformers require large datasets and struggle with noisy data, while complex architectures such as CNN-LSTM need further optimization and validation across varied datasets. Moreover, the adaptability of models to different tasks and domains requires additional exploration, as evidenced by the sentiment analysis using LeBERT and the classification of music genres with hybrid CNN and RNN models.

E. Conclusion

This paper explores the recent studies on classification tasks, particularly focusing on deep learning methodologies, highlighting their profound impact across various domains. Deep learning techniques, alongside their diverse variants, have showcased exceptional efficacy in pivotal tasks such as image recognition, sentiment analysis, and disease diagnosis. Through the integration of advanced computational techniques, feature selection methodologies, and hybrid model architectures, significant strides have been made in enhancing classification accuracy and efficiency. The broad spectrum of applications spanning healthcare, agriculture, disaster response, and beyond underscores the indispensable role of these methodologies in facilitating automated decision-making, pattern recognition, and data-driven insights. This review fosters the continual development of more effective and efficient classification algorithms and methodologies, benefiting researchers and practitioners in classification tasks.

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