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An Experimental-Based Review of Deep Learning in Multiclass Domains

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Abstract: Artificial intelligence (AI) is in a thriving phase, with machine learning emerging as a promising avenue towards achieving strong AI. Deep learning, a subset of machine learning, is gaining increasing popularity and success in various AI applications. Deep learning, a subset of machine learning and artificial intelligence, plays a central role in the Fourth Industrial Revolution (Industry 4.0). It stems from artificial neural networks and is known for its data-driven learning abilities. This paper projects an overview and the experimental results of deep learning methods in various studies across multi domains.

Index Terms – Machine Learning, Deep Learning, Artificial Neural Networks, Health care, Text Analysis

I. INTRODUCTION

Artificial intelligence (AI) has become pervasive in our daily lives, influencing various aspects. Researchers are increasingly drawn to the AI domain due to its wide-ranging applications. Traditionally, machine learning involved processing raw data, applying feature extraction techniques, and using classifiers, all of which required domain-specific expertise. However, this single-level processing approach sometimes led to less accurate results. Recently, deep learning methods have gained prominence for their ability to enhance accuracy and processing speed. Deep learning involves multiple layers of representation, with each layer being modified by non-linear modules, creating complex functions that reduce variations and enhance discrimination. Unlike traditional machine learning, deep learning's feature extraction layers are learned from data, not designed by human experts. Deep learning methods make use of multi-layered labeled data and neural network designs. They are capable of performing at levels above those of humans. These architectures don't require manual feature extraction because they can learn features directly from data. A deep neural network (DNN) employs multiple layers of units with meticulously crafted algorithms and architectures for optimal performance. It is at the forefront of AI development and continues to lead in various domains.

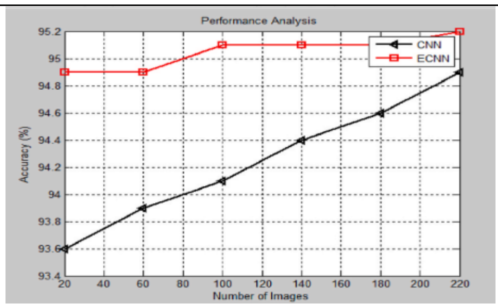
II. EXPERIMENTAL REVIEW

[1] Deep learning approach for segmentation and classification of blood cells using enhanced CNN

The study used the K-means algorithm and image processing techniques to segment and categorize blood cells. This is essential for using a total blood cell count to determine overall health. In the past, manual hemo cytometer counting required a lot of time and effort. Unsupervised data is analyzed using deep learning (DL), a subset of artificial intelligence and machine learning. White blood cells (leukocytes), which are also plentiful and distinguished by their dark red hue, serve as a defense against infections. To separate white blood cells, MATLAB aids in spotting variances in parameters like area, perimeter, mean, and standard deviation. With an average accuracy of 95% and an average precision of 0.93, author outperform previous CNN models in their classification of normal and abnormal blood cell pictures.
Authors proposed used Enhanced Convolution Neural Network (ECNN) for training and evaluating models with testing data. It is employed to enhance the classification and segmentation of blood sample images, resulting in improved diagnostic accuracy through deep learning. ECNN utilizes internal state memory to process input images and consists of finite and infinite impulse networks, both exhibiting dynamic behavior. Additional states are employed in these networks for storage, controlled by a neural network, often referred to as gated states or gated memory. In the healthcare sector, deep learning-based models like ECNN are valuable for early disease detection, as demonstrated in this research focusing on identifying normal and abnormal red blood cells. Traditional blood cell counting methods are time-consuming in comparison.

Accuracy Comparison of Existing & Proposed method.

SI.No	No. Of Images	ACCURACY	
		CNN	ECNN
1.	20	93.6	94.9
2.	60	93.9	94.9
3.	100	94.1	95.1
4.	140	94.4	95.1
5.	180	94.6	95.1
6.	220	94.9	95.2



Precision Comparison of Existing & Proposed method.

SI.No	No. Of Images	PRECISION	
		CNN	ECNN
1.	20	0.90	0.92
2.	60	0.90	0.92
3.	100	0.91	0.92
4.	140	0.91	0.93
5.	180	0.91	0.93
6.	220	0.92	0.93

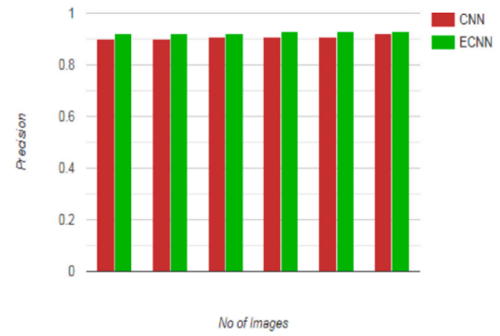


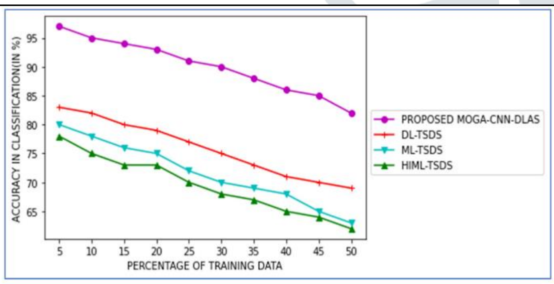
Figure :1 Experimental Results of Enhanced Convolution Neural Network approach

[2] Multi-Objective Genetic Algorithm and CNN-Based Deep Learning Architectural Scheme for effective spam detection

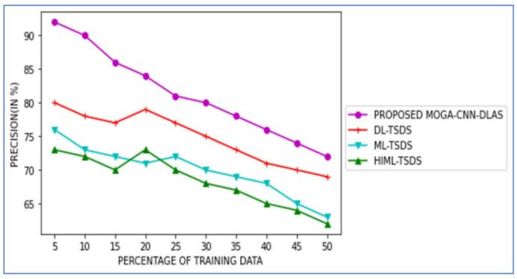
The paper addressed Spam problem for Twitter, as it not only causes annoyance but also contributes significantly to computer security issues, which causes major productivity losses. The authors offers a Multi-Objective Genetic Algorithm and a CNN-based Deep Learning Architectural Scheme (MOGA-CNN-DLAS) for identifying Twitter spam as solutions to this issue. The method is assessed using real datasets, such as the Twitter 100k dataset and the ASU dataset, while adjusting the training data ratio. Different metrics, including as accuracy, precision, recall, F-Score, RMSE, and MAE are measured.

The proposed MOGA-CNN-DLAS approach leverages the strengths of Support Vector Machines (SVM) over Logistic Regression for single-class classification, especially in Twitter spam detection where data often lacks linear separability. SVM uses a linear hyper plane to transform input data into higher-dimensional space, while Logistic Regression can suffer from over fitting. In this technique, MOGA-CNN-DLAS replaces Softmax regression with SVM at the output layer of a Convolutional Neural Network (CNN) effectively.

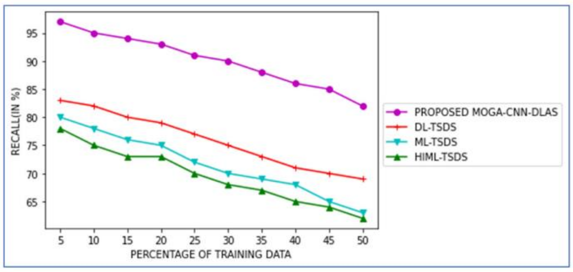
The approach is motivated by two key factors. First, it aims to tap into the potential of learning hidden semantics from large unlabeled data. Second, it addresses the challenge of resource limitations in the training process. The initialization of weights through Xavier initialization and the use of stochastic gradient descent back-propagation in training CNN play crucial roles. CNN is recognized for its ability to extract relevant lexical and syntactic features from Twitter data, contributing to the extraction of important features directly from the training data.



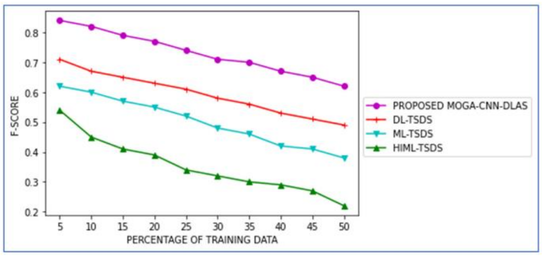
Proposed MOGA-CNN-DLAS Scheme - Accuracy under varying Percentage of Training Data in Twitter100k Dataset.



. Proposed MOGA-CNN-DLAS scheme - precision under varying percentage of training data in Twitter100k Dataset.



Proposed MOGA-CNN-DLAS scheme - recall value under varying percentage of training data in Twitter100k Dataset.



. Proposed MOGA-CNN-DLAS scheme - F-score under varying percentage of training data in Twitter100k Dataset.

Figure :2 Experimental Results of MOGA-CNN-DLAS approach

[3] A Deep Learning-Based Phishing Detection System Using CNN, LSTM, and LSTM-CNN

With phishing being a frequent and severe threat aimed at acquiring personal information, internet security is a significant concern. Phishers utilize false websites that look like authentic ones to acquire sensitive information from users, potentially causing financial harm and identity theft. Three deep learning-based methods are suggested in this paper: Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), and a combined LSTM-CNN method. High accuracy rates of 99.2% for CNN, 97.6% for LSTM-CNN, and 96.8% for LSTM are demonstrated by experimental data. The CNN-based approach performs better than the competition at detecting phishing.

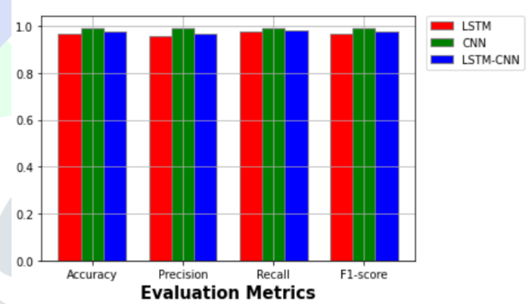
Long Short-Term Memory (LSTM) is an adaptive type of recurrent neural network (RNN) that utilizes memory cells to manage internal states in addition to conventional neurons. These memory cells are organized in layers and are connected in a repeating pattern. Each LSTM cell typically includes an input gate, controlling external data input and managing the internal state, and an output gate, determining whether the internal state is exposed to the outside. LSTM has proven effective in detecting phishing URLs. In the workflow of using LSTM for URL classification, data is loaded, preprocessed, and split. The LSTM model consists of an input layer with a 79-length vector, followed by an LSTM layer with 128 neurons serving as a memory component. Finally, a dense layer with a sigmoid function helps provide labels.

A **Convolutional Neural Network (CNN)** is a discriminative architecture designed for efficiently processing two-dimensional grid-based data, such as images and videos. In terms of processing speed, CNNs outperform standard neural networks (NNs) because they share weights in the temporal dimension, reducing computation time. This eliminates the need for generic matrix multiplications used in NNs, ultimately simplifying the network. In the workflow of using CNN for URL classification, the process begins by obtaining labeled training data for URLs, which is then randomly split into training and test sets. The next step involves creating the CNN architecture, including input, output, and layers, and training the model with the prepared data. After each convolution operation, a max-pool layer is used to capture essential features and convert them into a feature vector. Dropout regularization is added to prevent over fitting, and the model classifies the output using a sigmoid function.

The **LSTM-CNN** model combines Convolutional Neural Network (CNN) layers for feature extraction with Long Short-Term Memory (LSTM) layers for sequence prediction. A study has shown that incorporating a 1D convolution layer and an LSTM layer improves the accuracy of identifying malicious URLs compared to models using only LSTM layers. Therefore, for training URL features, the chosen architecture in this system involves 1D CNN and LSTM. In the CNN-LSTM workflow, the dataset is preprocessed, split into train and test sets, and normalized before being fed into the model. The model includes CNN and LSTM layers, along with a dense layer to prevent over fitting. Finally, the model classifies the results of the output using a sigmoid function.

The performance results.

Evaluation Metric	LSTM (%)	CNN (%)	LSTM-CNN (%)
Accuracy	96.8	**99.2**	97.6
Precision	95.9	99	96.9
Recall	97.5	99.2	98.2
F1-score	96.8	99.2	97.6



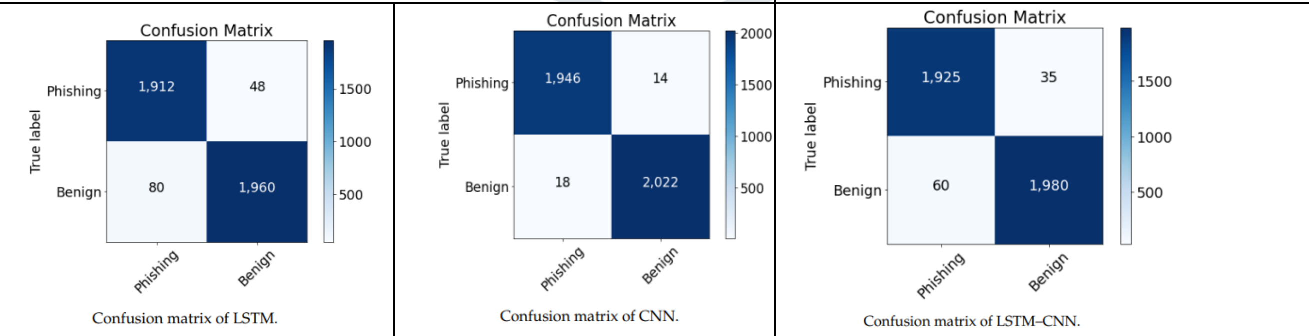


Figure :3 Experimental Results of LSTM,CNN and LSTM-CNN approach

[4] **Detection of fake news using deep learning CNN–RNN based methods**

Information that is purposefully untrue and can have a detrimental impact on politics and society is called fake news. Researchers use pre-trained word embeddings on different datasets together with deep learning methods like CNN, Bidirectional LSTM, and ResNet to stop its spread. To resolve class imbalances, they also use data augmentation through back-translation. According to the study, Bidirectional LSTM outperformed CNN and ResNet in identifying bogus news across all test datasets.

This research comprises two main phases. The first phase, illustrated in Figure 1, is the training phase. It starts by retrieving training data from the database. The training data undergoes a data cleansing process to remove poor-quality data. Afterward, data augmentation is applied to balance the class distribution. The augmented data is pre-processed and converted into word vectors using pre-trained word embeddings. These word vectors are then used to train deep learning models, including CNN, Bidirectional LSTM, and ResNet. The trained models are subsequently stored in the database for use in the testing phase.

The study examined the impact of data augmentation on model performance, and the results demonstrate a positive effect, particularly in enhancing performance consistency. Additionally, the study evaluated various deep learning methods, including CNN, Bidirectional LSTM, and ResNet, using four distinct datasets.

Datasets used in this study.

Dataset name	Cleaned	Augmented	Pre-processed	Fake news	Real news	Total
ISOT fake news dataset [13]	No	No	No	23.502	21.417	44.919
Fake news dataset [16]	No	No	No	10.413	10.387	20.800
Fake or real news dataset [20]	No	No	No	3.154	3.161	6.315
Fake news detection dataset [17]	No	No	No	2.135	1.870	4.005

Comparison of the proposed methods with the state of the arts on ISOT fake news dataset.

Author	Word embedding model	Classification model	Accuracy	Precision	Recall	F1-score
Ahmed et al.	TF–IDF	Linear SVM	92%	–	–	–
Ozbay & Alatas	TF–IDF	Decision tree	96.8%	96.3%	97.3%	96.8%
Ahmad et al.	LIWC	Random forest	99%	99%	100%	99%
Proposed model	fastText	CNN	99.88%	99.89%	99.88%	99.88%
Proposed model	GloVe	ResNet	99.90%	99.91%	99.90%	99.90%
Proposed model	**GloVe**	**Bidirectional LSTM**	**99.95%**	**99.95%**	**99.95%**	**99.95%**

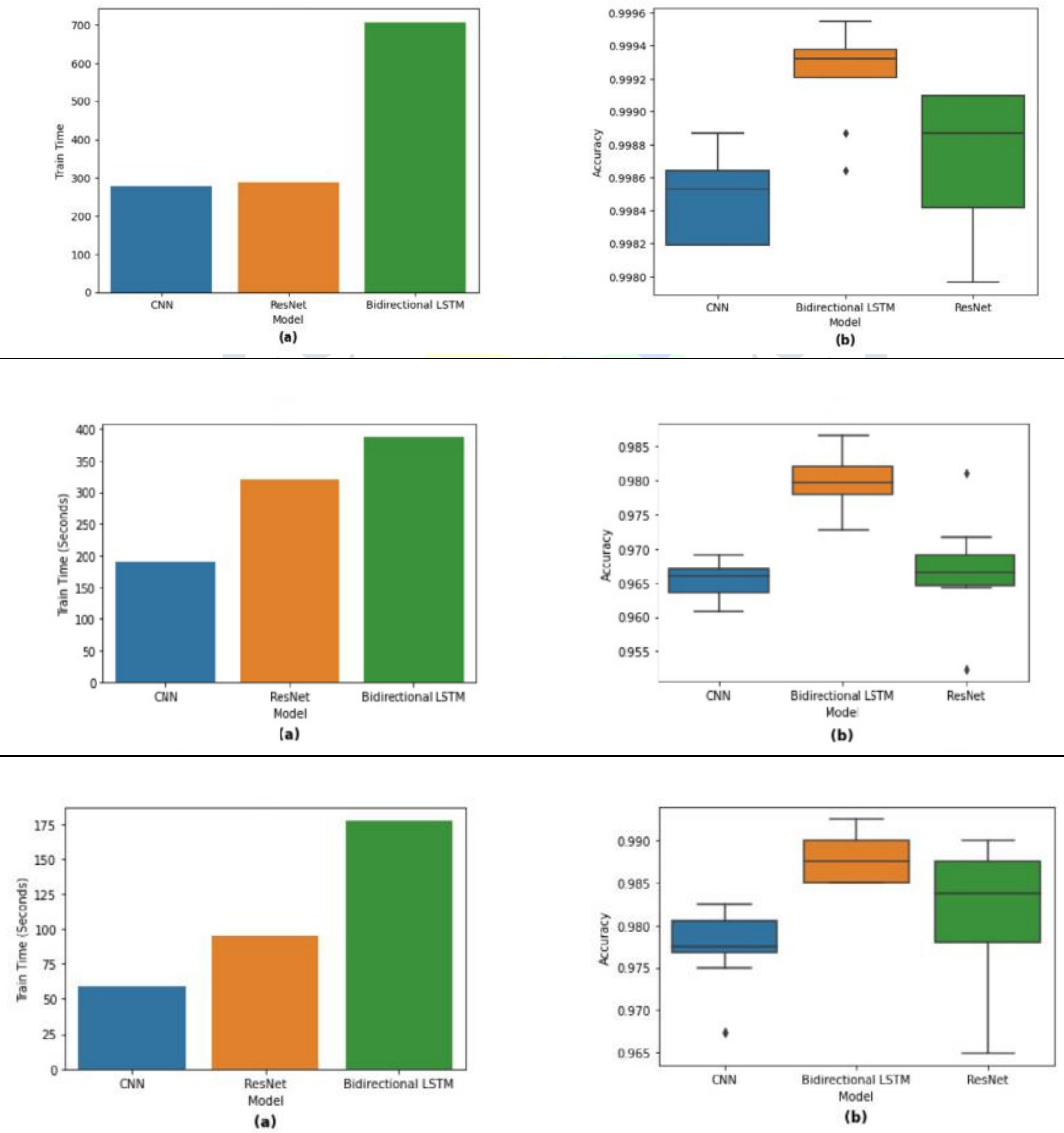


Figure :4 Experimental Results of CNN, ResNet and Bidirectional LSTM approach

III. DEEP LEARNING APPLICATIONS

Deep learning has found applications across a wide range of fields and industries. Some notable deep learning applications include:

Image Classification: Deep learning models can accurately classify images into various categories, such as identifying objects or recognizing handwritten digits.

Object Detection: They can detect and locate objects within images or video streams, essential for tasks like self-driving cars and surveillance.

Facial Recognition: Deep learning is used for recognizing and verifying faces, often seen in security systems and social media.

Machine Translation: Deep learning models like Transformers have greatly improved machine translation, with applications like Google Translate.

Chatbots and Virtual Assistants: NLP models power chatbots and virtual assistants, enabling natural language conversations with computers.

Sentiment Analysis: Analyzing text data to determine sentiment or emotions, useful for gauging public opinion or customer feedback.

Medical Image Analysis: Deep learning helps in diagnosing diseases through the analysis of medical images like X-rays, MRIs, and CT scans.

Drug Discovery: Deep learning models assist in drug discovery by predicting potential drug candidates and understanding molecular interactions.

Self-Driving Cars: Deep learning is a core technology for autonomous vehicles, helping them perceive the environment and make driving decisions.

Game AI: Deep learning enhances game AI by creating more intelligent and adaptive non-player characters (NPCs).

Recommendation Systems: Platforms like Netflix and Amazon use deep learning to provide personalized recommendations to users based on their past behavior.

Robotics: Robots employ deep learning for tasks such as object manipulation, navigation, and path planning.

Manufacturing: Deep learning is used for quality control and predictive maintenance in manufacturing processes, reducing defects and downtime.

Agriculture: It assists in crop monitoring, disease detection, and yield prediction, optimizing agricultural practices.
Energy:

IV. CONCLUSION:

Our review paper has provided a comprehensive overview of the current state of deep learning models when applied across multiclass domains. Through an extensive examination of existing research, we have identified several key takeaways: Model Performance, Model Variability, Data Augmentation etc.. Overall, our review highlights the significance of deep learning in advancing multiclass domain tasks. As the field continues to evolve, researchers and practitioners should stay updated with the latest developments and adapt models to suit specific domain requirements. We hope that this review paper serves as a valuable resource for those interested in deep learning across multiclass domains, fostering further innovation in this exciting and rapidly evolving field.

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