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Urdu Handwritten Words Recognition Using Machine Learning

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Abstract - The recognition of cursive or a running hand script is considered a difficult task in character recognition because it has a different representation style. Urdu originated from Arabic script, which is why it is much closer to Arabic script, has similar challenges and complications but with more intensity level. There are different styles of writing Urdu, but commonly Urdu alphabet is written in Nastalik script. This research work done on Convolutional Neural Networks with Mobile Net architecture with a Machine learning technique, i.e., Transfer Learning, makes it much easier. It is a technique where the model is developed for one task and then re-used as a starting point for different tasks. There are 603 images of Urdu Handwritten Words with 44 classes written by a different writer in datasets. The size of all images is 64*64, which is trained through the transfer learning technique. Code written in python using different python libraries like Keras, Ski learn, Numpy, etc., and accuracy is 90%, which is very efficient, later discussed in the last sections.

Keywords- Character Recognition, Machine Learning, Deep Learning, Transfer Learning, Cursive Script, Python, Mobile Net.

I. INTRODUCTION

Image classification is now a very complex problem area in machine learning. In this research, the topic is related to neural network techniques related to deep learning. Deep learning is seeking intention from researchers nowadays and successfully implements various real-world applications [1]. Deep learning algorithms can learn features from data that make deep learning in front of machine learning. Deep Learning DL extracts data features automatically in semi or unsupervised features learning algorithms and hierarchical feature extraction whereas machine learning generates features manually, which is time-consuming and a headache for the users [2]. There are a lot of classification problems that can be solved using different image datasets like images of the cat, dog, cars, fashion-related images, etc. [3] This study is based on a new data set of Urdu Handwritten Words and some printed words written in In Page with a different writing style. A total of 603 mixed Urdu word images in datasets have 64*64 dimensions with 44 classes and trained 49 samples to get results. Transfer Learning, a machine learning technique, helps solve complex problems easily and fast without worrying about having a large dataset.

Transfer Learning, a machine learning technique, aids in the easy and rapid resolution of complex problems. In addition, a novel transfer learning technique based on pretraining of hidden-unit CRFs (HUCRFs) is presented.[4]. Transfer Learning TL is a technique where a model is developed for one task and then re-use as a starting point of a different task [5]. This research shows how to perform transfer learning with Keras and DL using python, having its own generated dataset. There are several pre-trained models use in Transfer Learning that lies on large Convolutional Neural Network CNN. In TL, data can be divided into two phases, i.e., testing data and training data having two domains: (1) the target domain (2) the source domain. Target domain having testing samples and source domain consist of training samples [6].

Many languages are spoken in the world. Urdu is one of them and a cursive language like the Arabic language. Urdu Words' datasets are not very common as other types of datasets that are in trillion images uploaded on the internet. Urdu words datasets are very rare and not easily be available. There is not too much research on the Urdu language as compare to English languages. English datasets are available on a large scale because different types of English datasets are available on the internet. After all, many classification models and recognition models will be developed for training English datasets [7]. So, the Urdu language is a cursive language that very little work will be done on only having Urdu characters datasets for classification and recognition. Handwritten Urdu words are very rare as compare to printed words written in different InPage Font styles. That's why I choose to create my datasets of Urdu Words, both handwritten and printed Urdu words, which are randomly chosen from a dictionary. 603 different Urdu words have been written in fourteen different styles, where seven Styles are handwritten from different humans, and the other seven are written on Inpage with seven different font styles.

Machine learning (ML) is a very useful technology that has emerged in recent years. [8]. Most ML researchers can generate different approaches that help users to utilize these techniques to solve complex problems [9]. I use the Transfer Learning (TL) approach with a lightweight Mobile Net architecture to generate the most accuracy on Urdu Hand-Written Words Datasets. Besides a lot of datasets available on the internet for classification, I create datasets to add my benefactions.

This research adds a contribution to the field of neural networks, which is a versatile area of search, and a lot of datasets can be trained or classified in different neural network approaches [10]. The task is accomplished using its own generated datasets of Urdu Handwritten Words applying to Machine Learning. Algorithms enhance the field of computer science and give a little contribution to the research area.

This paper distributes into five sections. In the second section, literature review details, in the third section proposed work will be explained, in the fourth section based on experiments and results, and in the last section, conclusion and future work will be concluded.

II. Literature Review

A. Optical Character Recognition

The majority of recent research in the neural network domain is concentrated on character recognition systems or image processing. [11]. Different techniques and algorithms can be used in a character recognition system like hill-climbing techniques, OCR, Artificial Neural networks (ANN), fuzzy models, support vector machines (SVM). Different OCR systems are using different languages characters like English, Chinses, Arabic, Malayalam, and Urdu characters are some of the related work is given below:

In 2010 Arnol designed a handwritten recognition system using MATLAB's Neural Network Toolbox [12]. This design shows the need for more than one neural network to cover human handwriting habits fully. Also, the precision of character recognition depends on the resolution of the character projection.

Pradeep in 2011, in his paper, represented an offline handwritten recognition system without feature extraction that can be made by using a neural network [13]. The attempt is made to recognize English alphabets without feature extraction using a multilayer Feed-Forward neural network. The proposed system showed good recognition rates comparable to feature extraction methods.

Mehta 2016, in his paper, proposed a technique by using the concept of Artificial Neural Network and Nearest Neighbor Approach for character recognition from scanned images. The classification is done with an Artificial Neural Network with an accuracy of 95% [14].

K.P Prime Kumar, in his work, focuses on the recognition of handwritten Malayalam characters which the Hidden Markov Model (HMM) can recognize and Support Vectors Machines (SVM) with the system's accuracy gives maximum accuracy of 97.97% for SVM and 95.24% for HMM when tested on 1279 character samples [15].

Behram and Samad's work investigates the performances of a convolutional network on Persian handwritten recognition problems. They converting datasets elements into images of 64×64 pixels. It can use a single convolutional neural network and extend the convolutional neural network with an accuracy of 96.1% [16].

Helmy, in their proposed model, develops a lamping character recognition system using a backpropagation neural network. It gives an 80% accuracy rate for all laming characters [17]. Backpropagation is a kind of algorithm used for the supervised learning of artificial neural networks using gradient descent.

Tapos, in his paper, proposed a deep convolutional model to recognize Bengali handwritten characters. Bankalekha- isolated datasets are used. It tests digits, vowels, and all characters and gives a 95% average accuracy [18].

Deng Feng showed a framework for a New Tai Lue character recognition method using the Backpropagation neural network in his paper structure. It obtains some skew images using a scanner. Secondly, segmentation is carried out using text segmentation and word segmentation. Thirdly it generates local grey features using features vector [19].

M. Waqas Sagheer, Chun, Nicola, and Ching Suen proposed an approach to compound features and a support vector machine in the offline Urdu word recognition system, and compound features give structural and gradient features. Due to the cursive style in Urdu, a classification using a holistic approach is adapted efficiently. CENPARMI Urdu words datasets are used in this project. The high recognition accuracy of 97% is achieved [20].

Peng Xu showed how the Particle swarm optimizer (PSO) was used for standard handwritten English letters it has global optimization ability and backpropagation algorithms search advantage. It compares 140-pixel English letters with the backpropagation algorithm [21].

Tapobrata som recognizes handwritten numerals using fuzzy models it used fuzzy techniques to recognize the Hindi and English numerals with the accuracy of 95% and 98.4%, respectfully [22].

Das uses a neural network approach for optical character recognition. It can recognize even noise occurring. It involves simple edge detection and matching them with predefined patterns [23]. Das's first objective is to convert printed or handwritten characters into the machine-usable text to improve the process of collecting and storing data and second is to provide the algorithm that is better and faster with higher accuracy to recognize the characters.

B. Image Classification

There is very deep research on the image classification side [24]. Different approaches and techniques of neural networks, machine learning, are used such as Deep Learning, Convolutional Neural Network and Transfer Learning with different architectures like Alex Net, ImageNet, MobileNet models, Inception V3 was used. Different datasets of images were classifying like cats and dogs, fashion datasets, medical datasets, food images, MINIST datasets, traffic signs datasets were used for classifications. Some related work is given below:

M. Manoj Krishna used deep learning for image classification [25]. The researcher uses Alex Net architecture with a convolutional neural network. ImageNet database is used for test images. Deep learning-based image classification is very effective when used with Alex Net.

Tianmei and Guo proposed a simple convolutional neural network, analyzed different learning rate methods, and used different optimization algorithms to solve image classification parameters [26]. Convolutional neural networks demonstrated high performance on image classification.

Md. Tohidul Islam, Rahman, and B.M. Nafiz proposed a method that classifies food categories with images by using a convolutional neural network approach extracting spatial features from images. In his work, they used an inception v3 pre-trained model with ImageNet. This work has great importance along social media platforms, food and beverage companies [27].

Nadia Jamour explains a learning approach lies in convolutional neural networks for traffic signs image classifications. They adopt the Alex Net deep neural network model for classification with transfer learning [28]. Alex Net is 8 layers deep convolutional neural network and had a large impact on the field of machine learning.

Loussaief used two different approaches in machine learning for image classification one is Bag of Features (BoF) and Deep Learning with Convolutional Neural Networks [29]. They train ImageNet Datasets on the Alex Net model of CNN. They show how CNN is more performable than BoF with some experiments using Caltech datasets with classifying algorithms

Le Kang explains a Convolutional Neural Network (CNN) for document image classifications. They implement ReLU and dropout to gain the performance of CNN [30]. Previous approaches of handcrafted features are replaced by raw image pixels using CNN. This approach is effective even when large inner-class variations are present.

Al-Saffar reviewed on Deep Convolutional Neural Network in image classification. They can introduce the Deep Learning and Convolutional Neural Network (CNN) from rising to development and also explain the model, structure, pooling operation, and convolutional feature extraction of CNN [31]. This research also highlighted the current issues in the research methodology and also presented the future developments.

A Tien VO proposed an nLmF-CNN model, which the CNN model improves, and ConvNetJS architecture was used. They use online advertisement images with two classes, either yes or no. This work shows 85.74% of the proposed model [32].

Shin-Jye, Lee combines CNN with AdaBoost to gain the image classification problems with learning algorithms [30]. Firstly, deep CNN is used for feature extraction of images, and then AdaBoost is used to assemble the Softmax classifiers into recognizable images. This algorithm increased the accuracy of trained CNN models by 3%.

Gaoming Zhu, research lies in deep learning advanced framework Keras by using Convolutional Neural Network with twelve different kinds of texture images. They have minor original datasets with an unbalanced quantity [33]. They used different techniques to enhance and expand texture images like reflection enhancement, elastic transformation, random lighting, and other data augmentation techniques. The final accuracy achieved is 90%.

III. PROPOSED WORK

The proposed work is a novel approach to perform classifications or recognition of Urdu Hand-Written Words images with 44 different classes. Using a Transfer Learning Technique of Machine learning with Convolutional Neural Networks.

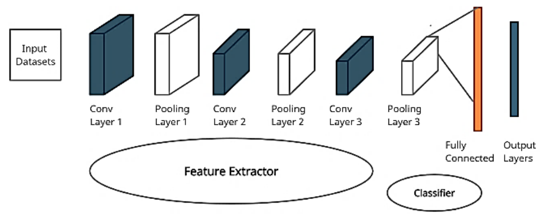


Fig 1: Proposed work

We used a deep learning approach i.e., convolutional neural network (CNN) with Keras framework, by using 603 images of Urdu Hand-Written Words. We use further transfer learning a pre-trained model with MobileNet architecture to classifying these images through convolutional layers, and then these layers are fully connected to get an output.

We train 433 samples, which are validated on 49 samples using a split validation technique. It is a variable in Keras which values lie between 0 and 1, which is proportionally splitting the training set with the variable value. The first set is used for training, while the second is used for validation. We try different Epochs and results close to 90%, which is much more advanced and suitable than the traditional classification methods with higher accuracy. We use one of the artificial neural network (ANN) types, which are Convolutional Neural Networks (CNN), with a machine learning approach, Transfer Learning (TL), and MobileNet Architecture [34].

A. Data set

We created our datasets of Urdu words and chose 44 different Urdu Words from the Urdu dictionary, and seven different peoples wrote these words, and these chosen words were written on InPage with 7 different font styles. There are a total of 603 images of 64* 64-pixel size having an RGB scale. We split these images into two categories for train and test. We also use datasets from the internet to check our model stability.

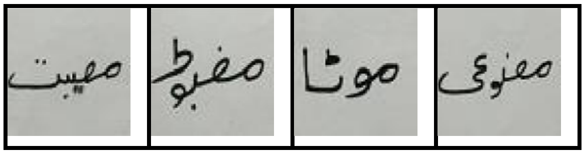
Fig 2: Urdu Handwritten words

From figure 2 we have one word of Urdu with fourteen different writing styles using seven styles related to handwritten by humans while the other seven are written in Inpage using 7 styling fonts. Like the above 44 words, datasets are arranged in the same manner. These datasets of a total of 603 images are trained on our proposed model using a transfer learning approach with mobile architecture.

Table I: Urdu words datasets (a) Hand-written words (b) Printed words

TOTAL URDU WORDS	CLASSES	HANDWRITTEN	PRINTED
603	44	339	264

(a)



(b)

B. Artificial Neural Network

ANN has commonly resembled the brain's neural structure [33], a nonlinear computational model to perform different tasks like decision-making, visualization, classification, prediction, etc. ANN has neurons that process elements and are then arranged in three interconnected layers as the input layer, a hidden layer with more than one layer, and finally, an output layer [35].

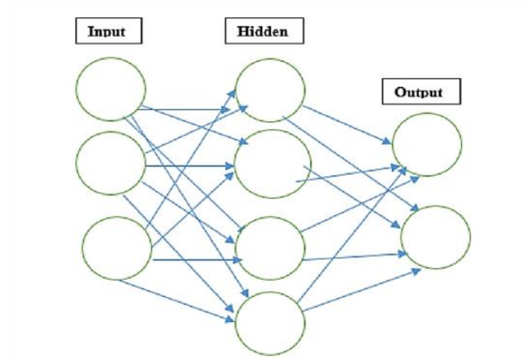


Fig 3: Artificial neural network

C. Experimental Setup

The environment of the network and framework includes (1) Programming Languages (Python 3), (2) Libraries, and (3) Methodology [36].

1. *Programming Language (Python 3)*: The programming language we choose for written code is Anacoda environment. It is a simple and open-source environment that includes the Python and R programming languages for solving computing problems [36]. It is used in data science, machine learning, etc. The aim of using this environment because of having the simplest package management and easy roll-out. We use python from Anacoda using JUPYTER Notebook.

2. *Libraries*: There are different libraries used for different scenes to help us in implementation. Python uses different libraries for performing different tasks like plotting graphs show the array and many other functions [37].

3. *Methodology*: One of the artificial neural network (ANN) types, which is a convolutional neural network (CNN) with a machine learning approach Transfer learning (TL), and MobileNet Architecture [38].

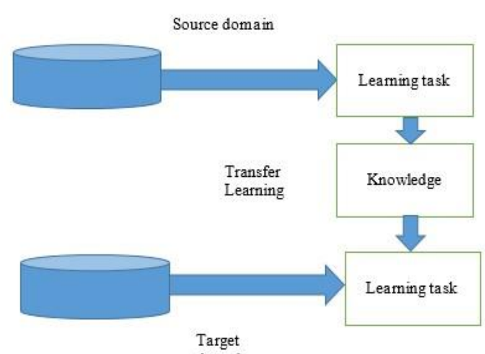


Fig 4: A transfer learning approach

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IV. EXPERIMENTS AND RESULTS

Results are shown on different Epochs, batch size, and accuracy on these epochs with a confusion matrix is determined. We choose 44 Urdu words randomly and then written by 7 different people with their different handwritings involve. These 44 words are also written in InPage with 7 Different font styles, which are 603 Urdu words of datasets. Then these datasets train on a convolutional neural network using MobileNet Classifier. We can train data on Different Epochs, and batch Size and good results will become out. Firstly, we try a run our datasets on batch size 50 and epoch size 20 results. We try different epochs using different batch sizes with high accuracy as shown in Table II. We also compare our architecture to train on different datasets of animals, flowers, etc., which shows our model stability and how accurate this model is to train different datasets.

Table II: Experimental Results

Sr.#	Epoch Size	Batch size	Accuracy	Time (seconds)
1	10	50	80%	244
2	20	100	81%	545
3	10	100	81%	332
4	20	50	80%	549

As the data loss problem occurs, the second experiment with an increase of epoch size and batch size with 20 and 100 is done, and we get much better results than the first experiments, and accuracy goes to 80%.

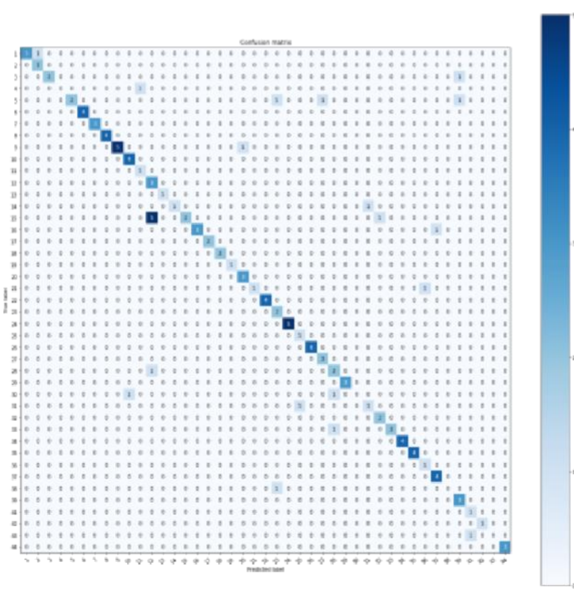

Fig 5: Confusion matrix

When we used more epochs or batch size models, overestimated conditions do not look good. Applying different experiments can easily understand data visualization and get better results with a higher accuracy rate. But the data loss problem occurs some time which is trying to reduce it [7].

Table III: Dataset results

Sr. #	Epoch size	Batch size	Accuracy	Time (seconds)
1	5	1000	72%	344
2	5	2500	75%	656

We also train MINST datasets of Chinese handwritten characters on the same model. We have each 64*64 images for classification. We train 15000 samples with 1080 samples used for validation. From figure 5, MINST Chinese handwritten datasets of which we train 15000 images were taken as samples while other 1080 images were used for validation. We train these datasets on the same model on which we train our self-generated datasets, as Table III we show the results of these datasets.

V. CONCLUSION AND FUTURE WORK

Image classification or recognition is a broad field of study in computer vision, machine learning, and neural networks. Image recognition will be used widely across industries, altering how we classify and search for visual information. This paper employs an Artificial Neural Network approach, specifically convolutional neural networks (CNN). CNN is a well-known approach, and the Keras Python library is used to classify our self-created datasets of 603 Urdu handwritten word images to train on our neural network because there is not easy availability of Urdu datasets. We used a transfer learning algorithm and a pre-trained model made by Google and the architecture used is MobileNet, a very reliable and light-weighted architecture with low computing power. We have done different experiments on our datasets by adjusting the size of epochs and batches up and down. Our results show 80% accuracy with a minor loss of data, but each experiment has a different time, which is not more than 550 seconds, around about 9 minutes. Furthermore, we use a MobileNet Architecture because it is very useful with mobile devices and other embedded devices. Also, it consumes less computing power and is a lightweight architecture. Some gaps in our proposed work can be filled by increasing the number of Urdu word images in the datasets and then training on the model. These datasets will also be trained on another model of a convolutional neural network by using Alex Net architecture, etc. also by using different techniques of artificial neural networks. There is a disadvantage of data loss that occurs and is being attempted to be removed in the future. It is safe to assume that image recognition technology will boost a quality advance for data search and classification in the future.

REFERENCES

[1] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural networks,* vol. 61, pp. 85-117, 2015.

[2] C.-K. Ngan and K. Bhuva, "A Framework and Decision Algorithm to Determine the Best Feature Extraction Technique for Supporting Machine Learning-Based Hate Speech Detection," in *International Conference on Intelligence Science*, 2021, pp. 15-28: Springer.

[3] S. K. Vishnoi, T. Bagga, A. Sharma, and S. N. Wani, "Artificial Intelligence enabled marketing solutions: A Review," *Indian Journal Of Economics & Business,* pp. 167-177, 2018.

[4] Y.-B. Kim, K. Stratos, R. Sarikaya, and M. Jeong, "New transfer learning techniques for disparate label sets," in *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 2015, pp. 473-482.

[5] A. Quattoni, M. Collins, and T. Darrell, "Transfer learning for image classification with sparse prototype representations," in *2008 IEEE Conference on Computer Vision and Pattern Recognition*, 2008, pp. 1-8: IEEE.

[6] T. Kaur and T. K. Gandhi, "Deep convolutional neural networks with transfer learning for automated brain image classification," *Machine Vision and Applications,* vol. 31, no. 3, pp. 1-16, 2020.

[7] K. A. El Dahshan, E. K. Elsayed, A. Aboshoha, and E. A. Ebeid, "Recognition of Facial Emotions Relying on Deep Belief Networks and Quantum Particle Swarm Optimization," *International Journal of Intelligent Engineering and Systems,* vol. 13, no. 4, pp. 90-101, 2020.

[8] H. Kour and N. K. Gondhi, "Machine Learning approaches for Nastaliq style Urdu handwritten recognition: A survey," in *2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)*, 2020, pp. 50-54: IEEE.

[9] J. Geng, X. Deng, X. Ma, and W. Jiang, "Transfer learning for SAR image classification via deep joint distribution adaptation networks," *IEEE Transactions on Geoscience and Remote Sensing,* vol. 58, no. 8, pp. 5377-5392, 2020.

[10] S. Hassan, A. Irfan, A. Mirza, and I. Siddiqi, "Cursive handwritten text recognition using bi-directional LSTMs: a case study on Urdu handwriting," in *2019 International Conference on Deep Learning and Machine Learning in Emerging Applications (Deep-ML)*, 2019, pp. 67-72: IEEE.

[11] D. J. Livingstone, *Artificial neural networks*. Springer, 2009.

[12] N. Kumar and S. Gupta, "Offline handwritten Gurmukhi Character recognition: a review," *International Journal of Software Engineering and Its Applications,* vol. 10, no. 5, pp. 77-86, 2016.

[13] R. Arnold and P. Miklós, "Character recognition using neural networks," in *2010 11th International Symposium on Computational Intelligence and Informatics (CINTI)*, 2010, pp. 311-314: IEEE.

[14] J. Pradeep, E. Srinivasan, and S. Himavathi, "Neural network based handwritten character recognition system without feature extraction," in *2011 international conference on computer, communication and electrical technology (ICCCET)*, 2011, pp. 40-44: IEEE.

[15] H. Mehta, S. Singla, and A. Mahajan, "Optical character recognition (OCR) system for Roman script & English language using Artificial Neural Network (ANN) classifier," in *2016 International Conference on Research Advances in Integrated Navigation Systems (RAINS)*, 2016, pp. 1-5: IEEE.

[16] K. Primekumar and S. M. Idiculla, "On-line Malayalam handwritten character recognition using HMM and SVM," in *2013 International Conference on Signal Processing, Image Processing & Pattern Recognition*, 2013, pp. 322-326: IEEE.

[17] F. Sarvaramini, A. Nasrollahzadeh, and M. Soryani, "Persian handwritten character recognition using convolutional neural network," in *Electrical Engineering (ICEE), Iranian Conference on*, 2018, pp. 1676-1680: IEEE.

[18] D. Singh and B. S. Khehra, "Digit recognition system using back propagation neural network," *International Journal of Computer Science and Communication,* vol. 2, no. 1, pp. 197-205, 2011.

[19] B. Purkaystha, T. Datta, and M. S. Islam, "Bengali handwritten character recognition using deep convolutional neural network," in *2017 20th International conference of computer and information technology (ICCIT)*, 2017, pp. 1-5: IEEE.

[20] V. Machine, "Editorial iii."

[21] M. Jameel and S. Kumar, "Offline recognition of handwritten urdu characters using b spline curves: A survey," *International Journal of Computer Applications*, vol. 157, no. 1, pp. 28-34, 2017.

[22] X. Teng, H. Dong, and X. Zhou, "Adaptive feature selection using v-shaped binary particle swarm optimization," *PloS one*, vol. 12, no. 3, p. e0173907, 2017.

[23] T. Das, A. K. Tripathy, and A. K. Mishra, "Optical character recognition using artificial neural network," in *2017 international conference on computer communication and informatics (ICCCI)*, 2017, pp. 1-4: IEEE.

[24] B. Wang, Y. Sun, B. Xue, and M. Zhang, "Evolving deep convolutional neural networks by variable-length particle swarm optimization for image classification," in *2018 IEEE Congress on Evolutionary Computation (CEC)*, 2018, pp. 1-8: IEEE.

[25] A. Indian and K. Bhatia, "A survey of offline handwritten Hindi character recognition," in *2017 3rd International Conference on Advances in Computing, Communication & Automation (ICACCA)(Fall)*, 2017, pp. 1-6: IEEE.

[26] M. A. Haq, G. Rahaman, P. Baral, and A. Ghosh, "Deep Learning Based Supervised Image Classification Using UAV Images for Forest Areas Classification," *Journal of the Indian Society of Remote Sensing*, vol. 49, no. 3, pp. 601-606, 2021.

[27] T. Guo, J. Dong, H. Li, and Y. Gao, "Simple convolutional neural network on image classification," in *2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA)*, 2017, pp. 721-724: IEEE.

[28] T. Pamula, "Road traffic conditions classification based on multilevel filtering of image content using convolutional neural networks," *IEEE Intelligent Transportation Systems Magazine*, vol. 10, no. 3, pp. 11-21, 2018.

[29] M. T. Islam, B. N. K. Siddique, S. Rahman, and T. Jabid, "Food image classification with convolutional neural network," in *2018 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS)*, 2018, vol. 3, pp. 257-262: IEEE.

[30] S. Loussaief and A. Abdelkrim, "Deep learning vs. bag of features in machine learning for image classification," in *2018 International Conference on Advanced Systems and Electric Technologies (IC_ASET)*, 2018, pp. 6-10: IEEE.

[31] B. B. Traore, B. Kamsu-Foguem, and F. Tangara, "Deep convolution neural network for image recognition," *Ecological Informatics*, vol. 48, pp. 257-268, 2018.

[32] S.-H. Wang, P. Phillips, Y. Sui, B. Liu, M. Yang, and H. Cheng, "Classification of Alzheimer's disease based on eight-layer convolutional neural network with leaky rectified linear unit and max pooling," *Journal of medical systems*, vol. 42, no. 5, pp. 1-11, 2018.

[33] S.-J. Lee, T. Chen, L. Yu, and C.-H. Lai, "Image classification based on the boost convolutional neural network," *IEEE Access*, vol. 6, pp. 12755-12768, 2018.

[34] G. Zhu, B. Li, S. Hong, and B. Mao, "Texture recognition and classification based on deep learning," in *2018 Sixth International Conference on Advanced Cloud and Big Data (CBD)*, 2018, pp. 344-348: IEEE.

[35] I. Gogul and V. S. Kumar, "Flower species recognition system using convolution neural networks and transfer learning," in *2017 Fourth International Conference on Signal Processing, Communication and Networking (ICSCN)*, 2017, pp. 1-6: IEEE.

[36] Y. Khoo, J. Lu, and L. Ying, "Solving parametric PDE problems with artificial neural networks," *European Journal of Applied Mathematics*, vol. 32, no. 3, pp. 421-435, 2021.

[37] J. Wang, L. Li, K. Liu, and H. Cai, "Exploring how deprecated python library apis are (not) handled," in *Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, 2020, pp. 233-244.

[38] A. Younis, L. Shixin, S. Jn, and Z. Hai, "Real-time object detection using pre-trained deep learning models MobileNet-SSD," in *Proceedings of 2020 the 6th International Conference on Computing and Data Engineering*, 2020, pp. 44-48.