A Machine Learning Driven Android Based Mobile Application for Flower Identification

Towhidul Islam[1], Nurul Absar[1](✉), Abzetdin Z. Adamov[2], and Mayeen Uddin Khandaker[3]

[1] Department of Computer Science and Engineering, BGC Trust University Bangladesh, Chittagong 4301, Bangladesh
towhidul@bgctub.ac.bd

[2] Center for Data Analytics Research (CeDAR), ADA University Baku, Baku, Azerbaijan
aadamov@ada.edu.az

[3] Centre for Applied Physics and Radiation Technologies, School of Engineering and Technology, Sunway University, Bandar Sunway, 47500 Selangor, Malaysia
mayeenk@sunway.edu.my

Abstract. In the field of Botany the research of flower classification scheme is an extremely significant topic. A classifier of flowers by maximum precision will also carry numerous enjoyments to human lives. However, there are tranquil a few disclaim in the identification of flower images due to the multipart conditions of flowers, the resemblance connecting the unusual flowers of species, and the variations surrounded by the similar species of flowers. The classification of flower is largely depend on the Color, shape and texture features which needs populace to choose features for classification and the accurateness is not extremely high. We were designed an Android application using machine learning techniques for flower identification. In this paper, based on Image Net model of DNN Tensor Flow Framework platform, to get better the accuracy of flower classification significantly, the Deep Neural Network (DNN) knowledge were used to retrain the flower category datasets. We were used ten category datasets. The accuracy of Image Net based MobileBetV2 model was 98.47% and proposed Deep CNN Model accuracy was 89.87% in our result. Any user can identify the flower by using our application from the flower images.

Keywords: Flower classification · Tensorflow · Keras · CNN · Feature extraction · Machine learning · MobilenetV2 · GoogLeNet

1 Introduction

Image recognition is one of the core fields in computer vision which can use the outcome for example hand writing recognition like in and fingerprint recognition

M. Mahmud et al. (Eds.): AII 2021, CCIS 1435, pp. 163–175, 2021.
https://doi.org/10.1007/978-3-030-82269-9_13

otherwise flush in extra significant studies for example medical researches etc., this value involving through the endeavour to facilitate must be involved for the classification method and by the amount of applications. In the cultivation of flowers, flower findings for apparent study, etc. applications of classification of flowers is used frequently.

Seed and bulb invention, flower trade, micro propagation, garden centre and preserved plants, and removal of important flowers oil comprises in the floriculture industry. Computerisation of flower classification is important in such belongings. Computerization of the categorisation of flower images is a essential job since these works are done physically and are very work comprehensive. There are more or less two millions and fifty thousand species of flowering plants as a named in the world. Categorise the plants by their flowers be able to be finished only by trained taxonomists and a lot of blooming flowers are detected in the park, backyard, wayside and various supplementary locations by skilled people also. People frequently must need flowers conduct manual or need the interrelated websites on the internet to peruse the knowledge with keywords because most of the public do not cover information concerning these flowers and in arrange to identify concerning them.

Artificial intelligence (AI) techniques in specific machine learning (ML) have been used over time to make easy classification, recognition and identification of patterns in biological data [33]. A multilayer neural network (NN) of CNN has achieved recognition in analysing image-based data [31]. In the midst of the current development of computing and superior understanding of AI different types of rule base and ML approaches have gained unrivalled awareness of the researchers in the last decade for the biological and healthcare big data mining, disease prediction and detection, text processing, disease management, and mobile health based app [25]. The main perception of deep learning (DL) is to be trained data representations through growing generalisation levels [25,31,33].

We are proposing a flower recognition approach with android application derived from image processing technique and deep convolutional neural network algorithm using Tensor Flow and Image Net in this work. People easily classify the flower image from our android device approach more accurately. We were used Google-11 and Tensorflow-5 dataset to implement of our proposed model including our local collection of flower.

2 Related Work

In recent years ML techniques have gained popularity in research for their abilities to predict patterns. They have been applied to many different fields including disease detection [12,34,39,40,44] and classification [11,17,30,47], elderly care [22,23] and fall detection [5,6,36], anomaly detection [8,18,51,52], biological data mining [31,33], cyber security [32], earthquake prediction [3,4], financial prediction [41], safeguarding workers in workplaces [25], text analytics [43,50], and urban planning [24].

Three primary contributions are discussed in [37]. Deep CNN for extracting the features and different machine learning algorithms for classifying objectives is used the categorization model to grow the performance of classifying of flower images in the first proposed model. In Second, the make use of image expansion for gaining enhanced substantiation consequences is established. KNN, Random Forest, Multi-Perceptions, and SVM are compared in last part of their research to measure the ability of the machine-learning classifiers. The author found 97.2% on oxford dataset using SVM and 98% accuracy on Oxford-17 using MLP.

Oxford 102 flowers dataset is used in [9] which containing of eight thousand one hundred eighty nine flowers images that fit in to 102 flower species. Four main steps were explained in this paper starting image augmentation, in gathering of images accustomed to settle in dataset images to generate further appropriate dataset for subsequently stage. To split the forefront from the backdrop image segmentation introduced. The accuracy rate was found 81.19% in this research.

Texture and color features used for flower classification by the author in [46]. From the segmented images, Texture and color features are extracted. GLCM method is used for Texture feature extraction and Color moment is used for color feature extraction. 95.0% accuracy of the system is found.

The authors uses a supervised model to extract flower content in [54] and [38] which consider the flower textures with graph cuts. The author in [29] used Novel Framework based Convolution Neural Network (CNN) to resolve this difficulty. They had implemented the algorithm on Oxford flower data set images from 102 species.

In [37] this author the flower sections are chosen to be individual in color (e.g., for example) and vary considerably in size, scale, and appearance developing a visual vocabulary that clearly represents different flowers (e.g., color, shape, and texture) for differentiate one flower from any more, Author can prevail over the ambiguities that be present stuck between flower sections. The results are presented in a data set of 1360 images with 17 flower species.

The [2] author used image classification using by Deep neural network (DDN) and five types of flowers that have been used the authors. They found the average result 90%. In [42] the system was developed using Python and Random Forest Classifier Method and Flower Identification used on RGB Histogram data. The Researchers found the proposed system is able to classify flower image with an average accuracy of 80.67% using 15 type of flower.

In [7] features based on color, texture, and shape on Image Classification and showed high result accuracy on oxford-17 dataset. Neural Network Based Image Processing is used for flower classification in [35]. They have proposed a method for classification of flowers based on Artificial Neural Network (ANN) classifier. GLCM and DWT of textural features is used of their proposed method. They got classification accuracy 85% more using GLCM features. The back propagation algorithm is used to train the neural network. Own dataset were created base of flowers of five classes, each one heaving ten flower images. They have got the result with MLP offers accuracy 87% with GLCM features.

ANN classifiers were studied in favor of the classification of flowers by the researcher in [20]. GLCM, DWT and Color features for instance normalized color histogram were used for textural features in their suggested model. A threshold based method is also used for flower image segmentation. A review of forty research work that make use of deep learning approaches used to different farming and food manufacture challenges performed by the authors in [26]. They study the specific agricultural harms with this research. The investigate result show that deep learning gives maximum accuracy.

A foreground background model is used in [10] where the segmentation is tested on five hundred seventy-eight flower species with two million fifty thousand images and hundred two flower species of OUFD with secure segmentation outcome. The contour matching algorithm is used getting the result in [48] which were not very encouraging of both flower and leaf images. In [13] K-means and OSTU segmentation algorithm were used. SVM and K-Nearest Neighbour (KNN) classifier is used for classifying the images to produce good results for those images.

In [28] the authors considered the transfer learning knowledge to retrain the flower category datasets based on Inception-v3 model of Tensor Flow platform which can very much increased the truthfulness of flower classification. Back propagation learning algorithm is used to trained Multilayer feed- forward networks in [21]. Color and shape features dependent segmentation model of flower is used by the authors in [13]. Training and testing were conducted on Oxford-102 flower and the findings illustrate a close to exact boundary recognition on a big set of images.

3 System Architecture

Our used system structural design of our proposed model is shown in following Fig. 1. This structural design showed that whole classification system in our model.

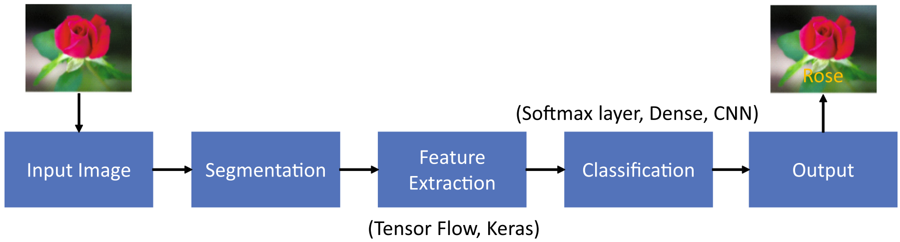

Fig. 1. System architecture in our proposed model.

4 Experimentation

4.1 Required Tools

Tensor Processing Unit (TPU). In May 2016 Google declared its TPU as an application of particular incorporated circuit that made exclusively for machine learning and tailored for TensorFlow [1]. In addition to the accessibility of the TPUs in Google Compute Engine, the 2nd generation announced in May 2017 which can deliver up to one hundred eighty teraflops of performance, and when prepared into clusters of sixty four TPUs, it is able to deliver 11.5 petaflops. The third-generation TPUs are announced by Google in May 2018 for supplying capable of four hundred twenty teraflops of execution and 128 GB HBM. Google were building TPUs easy to get to in beta on the Google Cloud Platform in February 2018.

Tensor Flow Lite. Tensor Flow Lite is a software stack exclusively for mobile expansion developed by Google in May 2017 [49]. A builder foretaste GPU inference engine for the mobile for the use of Open GL ES 3.1 Compute Shaders on Android devices and Metal Compute Shaders on iOS devices is released by Tensor Flow team in January 2019. Google introduced that their TensorFlow Lite Micro and ARM's tensor would be integration in May 2019.

Keras. Keras is an online resource documents that helps a Python interface for ANN which uses as an interface for the Tensor Flow library. Keras version 2.3 is used to support multiple backends, as well as Tensor Flow, R, Theano, Microsoft Cognitive Toolkit, and Plaid ML where the version 2.4, only TensorFlow is supported [27].

Features. Keras has various implementations of generally second-hand neural-network building. The code is generated on GitHub, and community support forums include the GitHub issues page, and a Slack channel [14].

ImageNet. An image dataset organized consistent with the WordNet hierarchy referred to ImageNet [19]. WordNet, possibly described "synonym set" or "synset" by using multiple words or word phrases. More than 100,000 synsets in WordNet are there wher 80,000+(majority) are nouns of them. Each synset provide on average 1000 images in ImageNet. ImageNet can offer tens of millions of modestly sorted images for most of the concepts in the WordNet hierarchy [45]. The need for more data the ImageNet project is encouraged by a rising response in the image and vision research field [53]. Ween vision Image Net as a valuable resource to researchers in the academic world, as well as educators around the world [15,16].

First training and testing dataset were divided from the input dataset where training and testing data were 80% and 20% respectively. We were used 11 category image data set in our research containing 4630 images where 3708 images for training set and 922images testing set. A sample of Google 11-flower dataset is shown in Fig. 2.

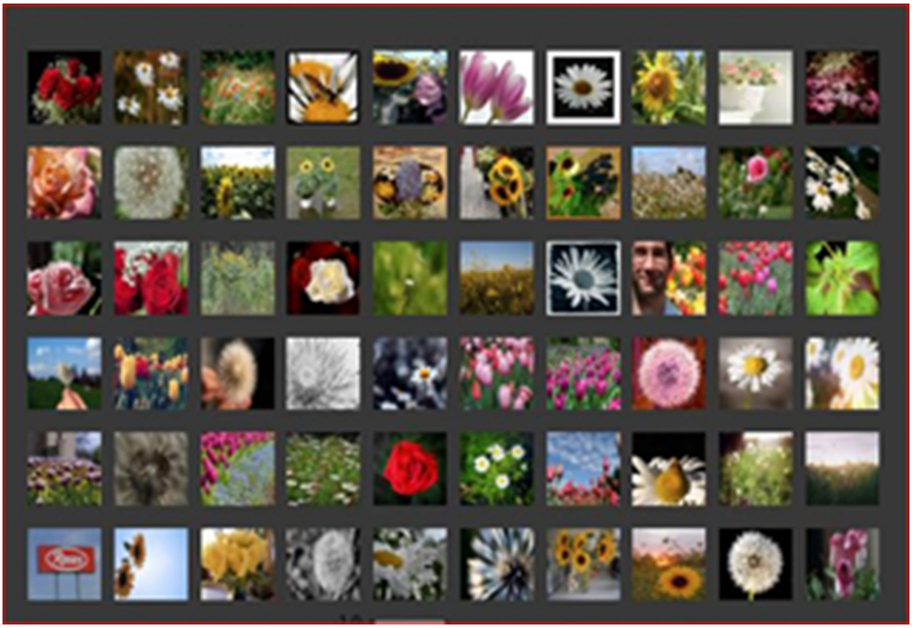

Fig. 2. Samples of 60 species of flowers in Google 11 -Flower Dataset.

We were proposed a two-step approach for the flower classification problem. The First step is designed multi stage CNN model. The model is constructed with input layer, five convolutional layers, seven rectified linear units (ReLu),

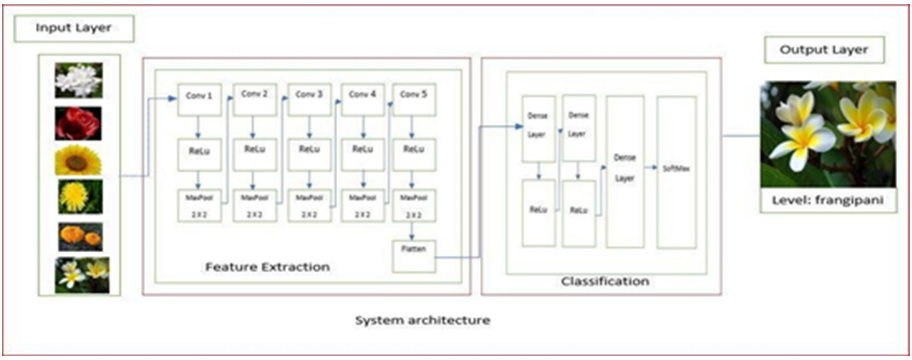

Fig. 3. The feature extraction and classification system architecture.

five stochastic pooling layers, two dense and one Soft Max output layer. The proposed CNN architecture uses five convolutional layers with same window sizes followed by an activation function, and a rectified linear unit for non-linearities. The feature extraction and classification system architecture has given in Fig. 3.

The Second Step is designed by ImageNet Model on MobileNetV2 which is shown in Table 1. In MobileNetV2, there are two types of blocks. One is residual block with stride of 1.

Table 1. ImageNet Model on MobileNetV2

Input	Operator	Output
$h \times w \times k$	1×1 conv2d, ReLU6	$h \times w \times (tk)$
$h \times w \times tk$	3×3 dwise $s = s$, ReLU6	$h/s \times w/s \times (tk)$
$h/s \times w/s \times tk$	linear 1×1 conv2d	$h/s \times w/s \times k'$

Another one is block with stride of 2 for down sizing. In both types of blocks 3 layers are there. 1×1 convolution with ReLU6 is the first layer. The second layer is the depth wise convolution. Without any non-linearity 1×1 convolution is the third layer also that is demanded that if ReLU is used over again. For all main experiments there is an extension factor t. where t = 6 for the post of Image. The internal output would get 64 × t=64 × 6 = 384 channels, if the input got 64 channels which is shown in Fig. 4.

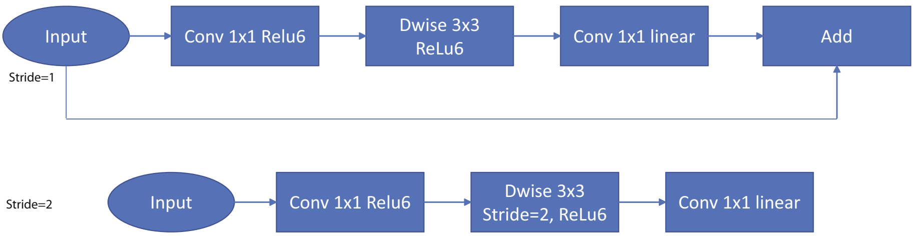

Fig. 4. Image input architecture.

5 Result and Discussion

The major purpose of our study is to properly demonstrate the flower image as of the traditional flower dataset. The suggested model of CNN was used to the

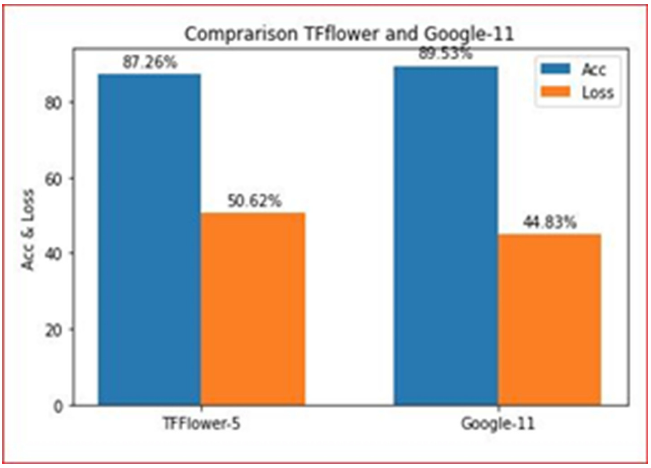

Fig. 5. Comparative results for Google-11 and Tensorflow-5 Flowers Dataset.

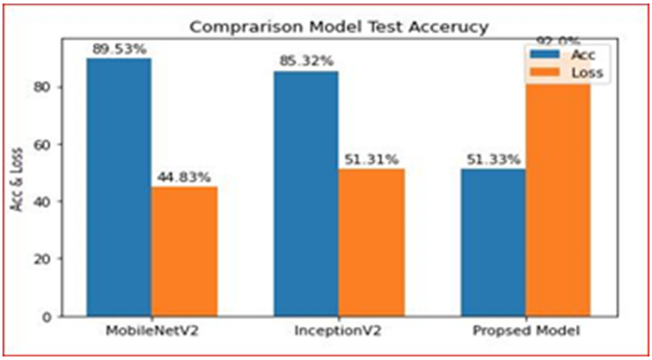

Fig. 6. Comparative results for Mobile NetV2, InceptionV2 and proposed model.

flower database for categorization. The database contains custom flower dataset were created by us in various orientations. The entire dataset were used with 10 classes. Dataset was having only flower images with reduced lighting provision. The training accuracy was 87.05%. and Image Net based MobileNetV2 model being trained Result accuracy was 98.07%. The comparative results for Google-11 and Tensorflow-5 Flowers Dataset has given in Fig. 5 and where the comparative results for Mobile NetV2, InceptionV2 and proposed model as shown in Fig. 6. Sample Output result using android application with accuracy as shown in Fig. 7.

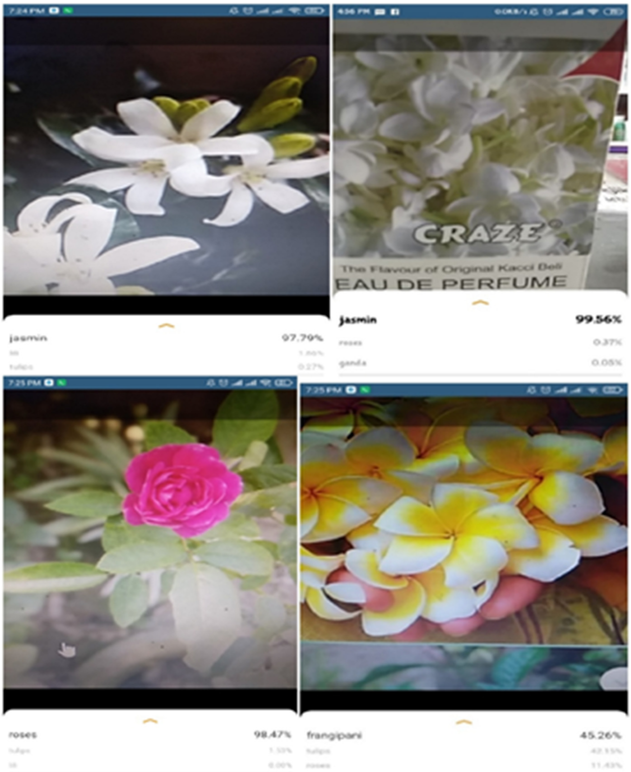

Fig. 7. Sample Output using android application with accuracy.

6 Conclusion and Future Work

The rapid development of technology, Artificial Intelligence has been useful in many fields. An application of machine learning and two different learning forms of machine learning explained the working principle of machine learning in our proposed work. In addition, it is shown that a research of flower identification and classification to initiate the workflow of machine learning in prototype recognition. The pattern recognition and its procedure in pattern recognition were clearly explained in our study. The CNN algorithm, which is a Deep learning algorithm from the ImageNet method, was used. Future work includes using other features of the flowers in classification, for example, texture and shapes. Other method for classification can be explored to provide more accuracy. Also, the database should be improved to contain more data. The system is very easy to use, therefore, it can be implemented for other objects.

Acknowledgement. This work was supported by the Sunway University Research Grant (GRTIN-IRG-05-2021). The authors also express their gratitude to the Department of Computer Science and Engineering, BGC Trust University Bangladesh.

References

1. Abadi, M., et al.: Tensorflow: a system for large-scale machine learning. In: 12th {USENIX} Symposium on Operating Systems Design and Implementation ({OSDI} 16), pp. 265–283 (2016)
2. Abu, M.A., Indra, N.H., Abd Rahman, A.H., Sapiee, N.A., Ahmad, I.: A study on image classification based on deep learning and TensorFlow. Int. J. Eng. Res. Technol. **12**(4), 563–569 (2019)
3. Al Banna, M.H., et al.: Attention-based bi-directional long-short term memory network for earthquake prediction. IEEE Access **9**, 56589–56603 (2021)
4. Al Banna, M.H., et al.: Application of artificial intelligence in predicting earthquakes: state-of-the-art and future challenges. IEEE Access **8**, 192880–192923 (2020)
5. Al Nahian, M.J., Ghosh, T., Uddin, M.N., Islam, M.M., Mahmud, M., Kaiser, M.S.: Towards artificial intelligence driven emotion aware fall monitoring framework suitable for elderly people with neurological disorder. In: Mahmud, M., Vassanelli, S., Kaiser, M.S., Zhong, N. (eds.) BI 2020. LNCS (LNAI), vol. 12241, pp. 275–286. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-59277-6_25
6. Al Nahian, M.J., et al.: Towards an accelerometer-based elderly fall detection system using cross-disciplinary time series features. IEEE Access **9**, 39413–39431 (2021). https://doi.org/10.1109/ACCESS.2021.3056441
7. Albadarneh, A., Ahmad, A.: Automated flower species detection and recognition from digital images. IJCSNS Int. J. Comput. Sci. Netw. Secur. **17**(4), 144–151 (2017)
8. Ali, H.M., Kaiser, M.S., Mahmud, M.: Application of convolutional neural network in segmenting brain regions from MRI data. In: Liang, P., Goel, V., Shan, C. (eds.) Brain Informatics. LNCS, pp. 136–146. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-37078-7_14
9. Almogdady, H., Manaseer, S., Hiary, H.: A flower recognition system based on image processing and neural networks. Int. J. Sci. Technol. Res. **7**(11), 166–173 (2018)
10. Angelova, A., Zhu, S., Lin, Y.: Image segmentation for large-scale subcategory flower recognition. In: 2013 IEEE Workshop on Applications of Computer Vision (WACV), pp. 39–45. IEEE (2013)
11. Aradhya, V.M., Mahmud, M., Agarwal, B., Kaiser, M.: One shot cluster based approach for the detection of COVID-19 from chest x-ray images. Cogn. Comput. 1–9 (2021). https://doi.org/10.1007/s12559-020-09774-w
12. Bhapkar, H.R., Mahalle, P.N., Shinde, G.R., Mahmud, M.: Rough sets in COVID-19 to predict symptomatic cases. In: Santosh, K.C., Joshi, A. (eds.) COVID-19: Prediction, Decision-Making, and its Impacts. LNDECT, vol. 60, pp. 57–68. Springer, Singapore (2021). https://doi.org/10.1007/978-981-15-9682-7_7
13. Chithra, P., Bhavani, P.: A study on various image processing techniques. Int. J. Emerg. Technol. Innov. Eng. **5**(5), 316–322 (2019)
14. Chollet, F.: Xception: deep learning with depthwise separable convolutions. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1251–1258 (2017)
15. Deng, J., Dong, W., Socher, R., Li, L.J., Li, K., Fei-Fei, L.: ImageNet: a large-scale hierarchical image database. In: 2009 IEEE Conference on Computer Vision and Pattern Recognition, pp. 248–255. IEEE (2009)

16. Deng, J., Li, K., Do, M., Su, H., Fei-Fei, L.: Construction and analysis of a large scale image ontology. Vis. Sci. Soc. **186**(2) (2009)
17. Dey, N., Rajinikanth, V., Fong, S., Kaiser, M., Mahmud, M.: Social-group-optimization assisted Kapur's entropy and morphological segmentation for automated detection of COVID-19 infection from computed tomography images. Cogn. Comput. **12**(5), 1011–1023 (2020). https://doi.org/10.1007/s12559-020-09751-3
18. Fabietti, M., et al.: Neural network-based artifact detection in local field potentials recorded from chronically implanted neural probes. In: Proceedings of IJCNN, pp. 1–8 (2020)
19. Fei-Fei, L., Deng, J., Li, K.: ImageNet: constructing a large-scale image database. J. Vis. **9**(8), 1037 (2009)
20. Hiary, H., Saadeh, H., Saadeh, M., Yaqub, M.: Flower classification using deep convolutional neural networks. IET Comput. Vis. **12**(6), 855–862 (2018)
21. Hsu, T.H., Lee, C.H., Chen, L.H.: An interactive flower image recognition system. Multimed. Tools Appl. **53**(1), 53–73 (2011). https://doi.org/10.1007/s11042-010-0490-6
22. Jesmin, S., Kaiser, M.S., Mahmud, M.: Towards artificial intelligence driven stress monitoring for mental wellbeing tracking during COVID-19. In: Proceedings of WI-IAT 2020, pp. 1–6 (2021)
23. Jesmin, S., Kaiser, M.S., Mahmud, M.: Artificial and internet of healthcare things based Alzheimer care during COVID 19. In: Mahmud, M., Vassanelli, S., Kaiser, M.S., Zhong, N. (eds.) BI 2020. LNCS (LNAI), vol. 12241, pp. 263–274. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-59277-6_24
24. Kaiser, M.S., et al.: Advances in crowd analysis for urban applications through urban event detection. IEEE Trans. Intell. Transp. Syst. **19**(10), 3092–3112 (2018)
25. Kaiser, M., et al.: iworksafe: towards healthy workplaces during COVID-19 with an intelligent Phealth app for industrial settings. IEEE Access **9**, 13814–13828 (2021)
26. Kamilaris, A., Prenafeta-Boldú, F.X.: Deep learning in agriculture: a survey. Comput. Electron. Agric. **147**, 70–90 (2018)
27. Ketkar, N.: Introduction to Keras. In: Deep Learning with Python, pp. 95–109. Springer, Berkeley (2017). https://doi.org/10.1007/978-1-4842-2766-4_7
28. Lakesar, A.L.: A review on flower classification using neural network classifier. Int. J. Sci. Res. **7**(5), 1644–1646 (2018)
29. Liu, Y., Tang, F., Zhou, D., Meng, Y., Dong, W.: Flower classification via convolutional neural network. In: 2016 IEEE International Conference on Functional-Structural Plant Growth Modeling, Simulation, Visualization and Applications (FSPMA), pp. 110–116. IEEE (2016)
30. Mahmud, M., Kaiser, M.S.: Machine learning in fighting pandemics: a COVID-19 case study. In: Santosh, K.C., Joshi, A. (eds.) COVID-19: Prediction, Decision-Making, and its Impacts. LNDECT, vol. 60, pp. 77–81. Springer, Singapore (2021). https://doi.org/10.1007/978-981-15-9682-7_9
31. Mahmud, M., Kaiser, M.S., McGinnity, T., Hussain, A.: Deep learning in mining biological data. Cogn. Comput. **13**(1), 1–33 (2021). https://doi.org/10.1007/s12559-020-09773-x
32. Mahmud, M.: A brain-inspired trust management model to assure security in a cloud based IoT framework for neuroscience applications. Cogn. Comput. **10**(5), 864–873 (2018). https://doi.org/10.1007/s12559-018-9543-3
33. Mahmud, M., Kaiser, M.S., Hussain, A., Vassanelli, S.: Applications of deep learning and reinforcement learning to biological data. IEEE Trans. Neural Netw. Learn. Syst. **29**(6), 2063–2079 (2018)

34. Miah, Y., Prima, C.N.E., Seema, S.J., Mahmud, M., Shamim Kaiser, M.: Performance comparison of machine learning techniques in identifying dementia from open access clinical datasets. In: Saeed, F., Al-Hadhrami, T., Mohammed, F., Mohammed, E. (eds.) Advances on Smart and Soft Computing. AISC, vol. 1188, pp. 79–89. Springer, Singapore (2021). https://doi.org/10.1007/978-981-15-6048-4_8
35. Mukane, S., Kendule, J.: Flower classification using neural network based image processing. IOSR J. Electron. Commun. Eng **7**, 80–85 (2013)
36. Nahiduzzaman, M., Tasnim, M., Newaz, N.T., Kaiser, M.S., Mahmud, M.: Machine learning based early fall detection for elderly people with neurological disorder using multimodal data fusion. In: Mahmud, M., Vassanelli, S., Kaiser, M.S., Zhong, N. (eds.) BI 2020. LNCS (LNAI), vol. 12241, pp. 204–214. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-59277-6_19
37. Nilsback, M.E., Zisserman, A.: A visual vocabulary for flower classification. In: 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2006), vol. 2, pp. 1447–1454. IEEE (2006)
38. Nilsback, M.E., Zisserman, A.: Delving deeper into the whorl of flower segmentation. Image Vis. Comput. **28**(6), 1049–1062 (2010)
39. Noor, M.B.T., Zenia, N.Z., Kaiser, M.S., Al Mamun, S., Mahmud, M.: Application of deep learning in detecting neurological disorders from magnetic resonance images: a survey on the detection of Alzheimer's disease, Parkinson's disease and schizophrenia. Brain Inform. **7**(1), 1–21 (2020)
40. Noor, M.B.T., Zenia, N.Z., Kaiser, M.S., Al Mahmud, M., Mamun, S.: Detecting neurodegenerative disease from MRI: a brief review on a deep learning perspective. In: Liang, P., Goel, V., Shan, C. (eds.) BI 2019. LNCS, vol. 11976, pp. 115–125. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-37078-7_12
41. Orojo, O., Tepper, J., McGinnity, T.M., Mahmud, M.: A multi-recurrent network for crude oil price prediction. In: Proceedings of IEEE SSCI, pp. 2953–2958. IEEE (2019)
42. Pardee, W., Yusungnern, P., Sripian, P.: Flower identification system by image processing. In: 3rd International Conference on Creative Technology CRETECH, vol. 1, pp. 1–4 (2015)
43. Rabby, G., Azad, S., Mahmud, M., Zamli, K.Z., Rahman, M.M.: TeKET: a tree-based unsupervised keyphrase extraction technique. Cogn. Comput. **12**(4), 811–833 (2020). https://doi.org/10.1007/s12559-019-09706-3
44. Ruiz, J., Mahmud, M., Modasshir, Md., Shamim Kaiser, M.: 3D DenseNet ensemble in 4-way classification of Alzheimer's disease. In: Mahmud, M., Vassanelli, S., Kaiser, M.S., Zhong, N. (eds.) BI 2020. LNCS (LNAI), vol. 12241, pp. 85–96. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-59277-6_8 Alzheimer's Disease Neuroimaging Initiative
45. Russakovsky, O., et al.: ImageNet large scale visual recognition challenge. Int. J. Comput. Vis. **115**(3), 211–252 (2015). https://doi.org/10.1007/s11263-015-0816-y
46. Shaparia, R., Patel, N., Shah, Z.: Flower classification using texture and color features. Kalpa Publ. Comput. **2**, 113–118 (2017)
47. Singh, A.K., Kumar, A., Mahmud, M., Kaiser, M.S., Kishore, A.: COVID-19 infection detection from chest x-ray images using hybrid social group optimization and support vector classifier. Cogn. Comput. 1–13 (2021). https://doi.org/10.1007/s12559-021-09848-3
48. Valliammal, N., Geethalakshmi, S.: Automatic recognition system using preferential image segmentation for leaf and flower images. Comput. Sci. Eng. **1**(4), 13 (2011)

49. Vincent, J.: Google's new machine learning framework is going to put more AI on your phone (2017). https://www.theverge.com/2017/5/17/15645908/google-ai-tensorflowlite-machine-learning-announcement-io-2017
50. Watkins, J., Fabietti, M., Mahmud, M.: Sense: a student performance quantifier using sentiment analysis. In: Proceedings of IJCNN, pp. 1–6 (2020)
51. Yahaya, S.W., Lotfi, A., Mahmud, M.: A consensus novelty detection ensemble approach for anomaly detection in activities of daily living. Appl. Soft Comput. **83**, 105613 (2019)
52. Yahaya, S.W., Lotfi, A., Mahmud, M.: Towards a data-driven adaptive anomaly detection system for human activity. Pattern Recogn. Lett. **145**, 200–207 (2021)
53. Yang, K., Qinami, K., Fei-Fei, L., Deng, J., Russakovsky, O.: Towards fairer datasets: filtering and balancing the distribution of the people subtree in the ImageNet hierarchy. In: Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, pp. 547–558 (2020)
54. Zhou, H., Zheng, J., Wei, L.: Texture aware image segmentation using graph cuts and active contours. Pattern Recogn. **46**(6), 1719–1733 (2013)