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EDITORIAL

Editorial of the Special Issue: Brain-like computing for medical applications

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Medical applications are increasing day by day but the necessity for more autonomous applications is always a challenge in the real world. The human brain works autonomously and takes decisions, so developing applications which work like the human brain is a key step to the autonomous medical world. In this special issue, the focus is to perform computing in medical applications in the way a human brain does. This can be achieved using artificial neural networks and different algorithms of artificial intelligence along with classification and segmentation. Deep learning and machine learning algorithms performed brain-like computing in medical applications with improved accuracy.

Smart healthcare system—a brain-like computing approach for analyzing the performance of detectron2 and PoseNet models for anomalous action detection in aged people with movement impairments by Divya, R. and J.D. Peter performed object detection and recognition of abnormal activities using the estimation of real-time pose models with the help of complex vision analysis. Object detection is performed by creating bounding boxes using a filter based upon a deep learning model named Detectron2. Different normal and abnormal activities are distinguished using PoseNet model and evaluation of performance is tested.

An improved framework for brain tumor analysis using MRI based on YOLOv2 and convolutional neural network by Sharif, M.I., et al. used four phases for brain tumour detection. The phases are enhancement of lesion, feature selection and extraction for classification, localization, and segmentation. For noise removal in images, a homomorphic wavelet filer is used. The extracted features from the pre-trained model of inception-v3 and other informative features are selected by the use of NSGA (non-dominated sorted genetic algorithm). YOLO-v2 inception-v3 model is used for the localization of the tumour and then the features are extracted by depth concentration layers of YOLO-v2 and inception-v3 models. Once the images are localized, these are passed to McCulloch's entropy method for the segmentation of the region of the tumour.

A decision support system for multimodal brain tumor classification using deep learning by Sharif, M.I., et al. developed an automated deep learning method used for the multi-class classification of brain tumours. For the realization of Densenet201, a pre-trained model of deep learning is tuned and then trained using deep transfer of learning in an imbalanced manner. The features are extracted from the average pool layer and two new feature selection techniques are proposed. The techniques are EKbHFV (entropy kurtosis-based high feature values) and MGA (modified genetic algorithm). The features extracted from MGA are refined using the threshold function and finally SVM classifier is used for multiclass classification.

EEG data augmentation for emotion recognition with a multiple generator conditional Wasserstein GAN by Zhang, A., et al., developed a multi-generator conditional Wasserstein

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GAN model designed to cover the distribution of real data using multiple generators.

Stomach Infections Segmentation and Classification Using Uncertainty Aware Deep Neural Network by Javeria Amin, M.S., Eman Gul, and Ramesh Sunder Nayak presented a deep semantic segmentation model for the three-dimensional segmentation of stomach infections. The model uses deep labv3 as an addition to the ResNet-50 model. The training of the model is performed with ground filters and in the testing phase, pixel-wise classification is performed.

Evolutionary multiple instance boosting framework for weakly supervised learning by Bhattacharjee, K., M. Pant, and S. Srivastava, presented an enhanced framework of multiple boosting named Evolutionary MILBoost uses different evolutions for the optimization of weak classifiers or estimators of weights in the framework.

Comparative performance analysis of quantum machine learning with deep learning for diabetes prediction by Gupta, H., et al., developed two models of prediction that are proposed which are applied using deep learning and quantum machine learning approaches.

A federated approach for detecting the chest diseases using DenseNet for multi-label classification by Priya, K. and J.D. Peter, presented a model for chest disease detection using DenseNet. The dataset used here is taken from Kaggle. The pre-trained models are used with transfer approach learning to improve performance. DenseNet121 is integrated into the pre-trained model. For the visualization of defected parts, gradCAMS are used.

A weighted least squares optimization strategy for medical image super resolution via*multiscale convolutional neural networks for healthcare applications* by Goyal, B., et al., suggested a model for lesion localization in which multi-scale Convolution Neural Networks are introduced where the least weighted squares optimization approach is used along with the medical resolution approach. By training CNNs, an SR model is designed which performs wavelet decomposition of all optimized images for the representation in multiple scales. The trained CNNs then regress the multi-scale representations of wavelets from LR medical images.

A deep network designed for segmentation and classification of leukemia using fusion of the transfer learning models by Saleem, S., et al., proposed a deep learning modified approach for the segmentation and classification of leukocytes. This process is carried out in two steps: preprocessing in terms of classification and segmentation. Preprocessing is done by generating synthetic images with the help of GAN (generative adversarial network) and color transformation by normalization. The optimal deep features are extracted using different pre-trained models, e.g., DarkNet53 and ShuffleNet. Further, features are extracted and selected using PCA and these are then combined for the classification of leukocyte cells.

Categorizing white blood cells by utilizing deep features of proposed 4B-AdditionNet-based CNN network with ant colony optimization by Shahzad, A., et al., presented an improved process of classification for white blood cells in which different approaches are used including CNNs, preprocessing, algorithms for feature selection, and many classifiers. While doing preprocessing, CLAHE (contrast limited adaptive histogram equalization) is done to the input images. For feature extraction, CNN is designed and trained with ResNet50 and EfficientNetB0 networks. For selecting the best features, the ant colony optimization algorithm is used and then the results are passed to SVM and QDA (quadratic discriminant analysis) for classification purposes.

Brain tumor detection and classification using machine learning: a comprehensive survey by Amin, J., et al., presented a survey of brain tumour detection using MRI (magnetic resonance imaging). The survey discussed brain anatomy, available datasets, and techniques of enhancement, feature extraction, segmentation, and classification for the analysis of brain tumours.

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