Abstract
Brain tumors are among the most grave and intricate diseases to be diagnosed and treated. Therefore, timely and accurate diagnosis of such tumors is critical for management of patients. Nowadays, the diagnosis of such conditions is mostly based on the interpretation of MRI images, which is a tedious and inconsistent task. Machine learning (ML) techniques, which were developed to assist in the automatic diagnosis, are often ineffective for high-dimensional medical images, are very specific in terms of the required feature engineering, and have low robustness to changes in the imaging conditions. This study covers in detail the design, development, and clinical evaluation of a Deep Convolutional Neural Network (DCNN) aimed at fully automating the diagnosis of brain tumors using MRI data. The key distinction of the proposed DCNN architecture is that, unlike conventional ML approaches, this model has an end-to-end learning framework that can automatically detect and refine relevant features directly from MRI images which helps in diagnosis and reduces manual effort. The model was trained and evaluated on a large scale brain tumor MRI dataset that is comprised of SARTAJ, FIGSHARE and BraTs datasets which are some of the most widely used US brain tumor MRI datasets. In order to provide a fair and accurate performance evaluation, the common transfer learning models of ResNet50, XceptionNet, ResNet101, EfficientNetB0, and DenseNet121 were utilized. In addition, other blended structures such as InceptionV3 with VGG19 and EfficientNetV2M with DenseNet121 were also examined. The proposed model of the DCNN has obtained the highest diagnostic accuracy which is equal to 98.40% and has demonstrated efficiency with a very low cost of computation of roughly 1.29 seconds. In this work, the proposed DCNN maintained a better performance than either of the pretrained models taken separately or the pretrained models arranged in two or more concatenated architectures, which were the only such constructions reported in the literature involving the same dataset as this one. Conclusive experimental results demonstrate that DCNNs hold the potential of revolutionizing the diagnosis of brain tumor by providing a fast, accurate, and non-expensive solution to radiologists, thus empowering them to make better informed decisions.
Such results open new avenues for development of patient-oriented solutions involving advanced deep learning methods into the CT's routine practice which also helps advance the field of medical imaging.