A Convolutional Neural Network based Feature Extractor with Discriminant Feature Score for Effective Medical Image Classification

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Abstract

In Computer-Aided Diagnosis (CAD) systems, major role is played by classification of medical images. Conventional methods uses texture features, color and shape information in a combined manner for classification. These methods are problem specific and in medical images, they have shown their complementary, which makes the systems inability to make high-level problem domain concepts representation and they are having worst model generalization ability. In recent days, because of its admirable performance in different fields, great attention is gained by convolutional neural networks (CNN). However, complete training of a novel deep CNN model is concentrated in recent works to target issues with restricted data and time consuming issues. Various investigations are done for rectifying those drawbacks of existing techniques. They utilized a CNN models a feature extractor for feature representation construction which is helpful for classification and they are successfully applied in remote sensing scene classification. For region classification, in order to in cooperate pre-trained CNN model's multilayer features, fusion strategies are used in this investigations. Fully connected and diverse convolutional layers deep features are haul out by using pre trained CNN model as a feature extractor. Then, convolutional features are constructed by computing multi-dimensional enhanced discriminative feature score. At last, for classification, regression based kernel discriminant method is integrated with fully connected layers features and convolutional layers intermediate level features. With high-resolution remote sensing data sets, via MATLAB, proposed technique is evaluated for validation and better performance is exhibited in contrast with fine-tuning CNN models, fully trained CNN models and other related works.

Key Words: Feature Fusion, Multi-dimensional Features, Convolutional Neural Networks (CNN), Discriminative Feature Score, Medical Image Classification.

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Introduction

In machine learning field and application-specific studies, image understanding using computer programs has become an attractive and active topic due to the rapid enhancements made in the fields of digital image acquisition and storage [1]. A fast as well accurate annotation or medical image grading system is needed for developing an intelligent Computer-Aided Diagnosis (CAD) system in various medical fields.

For instance, in United States, huge amount of people are diagnosed with skin cancer every year. Lives of many can be saved if they are detected in earlier stages [2]. Image information are unified by the recent enhancements in medical image classification. For specific clinical applications or in medical research, better usage of some type of image information are facilitated by this.

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A wide classes of images are covered using a term 'medical image' with very different applications and very different underlying physical principles [3]. There will be difference in images used for healthcare and medical research and histological section's microscopic images, video images of remote consultation. There will be difference between body radioisotope images and eye image taken with a fundus camera.

In principle, all the relevant information of specific patients are brought together as a single representation of that patient, irrespective of their form in medical image registration. That is used a multimedia electronic patient record, which has an implicit information about temporal and spatial relationship between all image information [4]. This is made difficult by large amount of temporal and spatial resolutions and different image's field view and not yet demonstrated the clinical benefit of such an techniques.

In database and pattern recognition analysis are the important applications of Automatic diagnostic systems, which aims to assist physicians in making diagnostic decisions. Various diseases are diagnosed using automated diagnosis. For various medical data including medical images and signals, automated diagnostic systems are applied [5].

In medicine in diagnostic and teaching purposes, an important role is played by classification of medical images. Various imaging modalities are utilized for these purposes. Using both color as well as grey-scale medical images, various classifications are created for medical images.

From huge amount of data, extraction of knowledge is referred as data mining. With knowledge extraction techniques, it used visualization, machine learning and statistical as well as other data manipulation [6]. In data, relationship among hidden pattern and data are computed using this. For research enhancements, possibilities are created using digital data within the pictures actual communication systems.

In a health record of a patient, medical images forma vital component and are used in handling, processing and manipulation of data using computers [7]. Base for the development of computer-assisted radiology is formed by this, Decision support systems are used make further enhancements, which are useful in making a decisions for diagnosis with relevant knowledge.

In recent days, r Machine Learning (ML) rapid progress is shown in the fields of Artificial Intelligence (AI). In medical fields like image retrieval and analysis Techniques, image-guided therapy, image segmentation, image registration, image fusion, image interpretation, computer-aided diagnosis, medical image processing [8], AI and ML techniques plays an important role. From images, information are extracted using ML techniques and efficient as well as effective representation of information can be done.

Accurate prediction and diagnosis by doctors are assisted as well as facilitated using AI and ML techniques, diseases risk are faster and that has to prevented in time. Analysis of generic variations by doctors and researchers facilitated by enhancements of these techniques [9]. There are conventional algorithms in these techniques without learning like Generative Adversarial Networks (GANs), Extreme Learning Model (ELM), Long Short term Memory (LSTM), Recur-rent neural Network (RNN), Convolutional Neural Network (CNN), Neural Network (NN), KNN, Vector Machine (SVM) etc.

Raw form processing of natural images are limited by former algorithms and they are time consuming and it requires a knowledge of an expert. Feature tuning needs lots of time. The later calculations are taken care of with crude information, programmed highlights student and quick [10]. These calculations attempt to get familiar with different degrees of reflection, portrayal and data consequently from enormous arrangement of pictures that show the ideal conduct of information. Although mechanized recognition of infections dependent on traditional strategies in clinical imaging has been indicated noteworthy exactnesses around for quite a long time, however new advances in AI procedures have touched off a blast in the deep learning [11]. Deep learning based calculations indicated promising execution too speed in various spaces. So in this exploration work focus and give enhancement for characterizing the medical images utilizing the pre-prepared Convolutional Neural Network.

In this investigation, pre-trained CNN is used as a feature extractor with discriminant feature score, therefore over-fitting may not occur as it is considered as unsupervised feature learning process. However, there are very lesser work to compute advantages of CNN model in remote sensing classification. Here, pre-trained CNN has been used as a feature extractor and provided with higher attention to exploit feature scored to various layers and construct discriminative feature specification for image classification. As well, this work computes ability of feature representation. To achieve this, pre-trained CNN is used here and score features are fused to construct feature representation in proposed CNN model. Alike of previous works, the essential contribution of this investigation is listed below:

1. To construct a discriminative feature score (DFS)in every layer of pre-trained CNN.
2. Fusing this feature extractor in various layers of pre-trained CNN for medical image classification.
3. The feature representation are constructed at various levels of features from pre-trained CNN models.

The remaining work is organized as: Section 2 shows background study related to this investigation on feature extraction and classification model in medical domain. Section 3 depicts the fusion of feature extractor and classification model. Section 4 shows numerical results and discussions and Section V is conclusion of proposed model with directions for future extensions.

Literature Review

For increasing the performance of image classification, lot more methods of medical image classification are implemented in the past few years. Review of some recent medical image classification algorithms are presented in this section.

Li et al [12] classified lung image patches via implementation of customized Convolutional Neural Networks (CNN) having shallow convolution layer with interstitial lung disease (ILD). On the other hand, from lung image patches, intrinsic image features are learned efficiently as well as in an automatic manner using this customized CNN framework, which is highly suitable for classification. Other medical image or texture classification can also be done by generalizing the same architecture.

Zaıane et al [13] implemented an association rule mining based new classification technique. On a real dataset like medical images database, experimented this association rule-based classifier. A pre-processing phase of a proposed system mines the resulted transactional database and resulted association rules are organized in final phase of a classification model. More than 80% of accurate results can be produced using this proposed technique as shown in experimental results. In implementing accurate data mining architecture of image classification, importance of data cleaning phase is shown by this work.

Hoi et al [14] simultaneously selected a number of informative examples by applying Fisher information matrix in a presented a framework of "batch mode active learning". The submodular functions property based efficient greedy algorithm is proposed for identifying unlabeled subset examples, which may results in huge loss of fisher information. When compared with state-of-the-art algorithms of active learning, effectiveness of proposed batch mode active learning algorithm is shown by empirical studies with five UCI datasets and one real-world medical image classification.

Kumar et al [15] used an ensemble of different convolutional neural network (CNN) architectures for introducing a technique to classify medical images. For a specified classification task, optimum image features are learned using a state-of-the-art image classification technique called CNN. Various semantic image representation are learned by various CNN architectures and so, extraction of high quality features are enabled by ensemble of CNNs. For fine-tunnig CNNs, a new feature extractor is developed in this technique, which are initialized with huge dataset of natural images. 3

From natural images, generic image features are leveraged using this process, which are fundamental of every image and they optimized for various medical imaging modalities. Numerous multiclass classifiers are trained using this features. Unseen images modalities are predicted by fusing posterior probabilities of multiclass classifiers. Image CLEF 2016 medical image public dataset with 30 modalities, 6776 training images and 4166 test images are used for experimentation and greater accuracy are produced using our fine-tuned CNNs ensembles. On the same benchmark dataset, better accuracy are produced using this ensemble.

Pourghassem et al [16] used a perfect set of different shape and texture features for implementing a two level hierarchical medical image classification technique. Further, proposed a directional histogram as well as tessellation- based spectral feature. In hierarchical classifier, at every level, created a new merging scheme and multilayer perceptron (MLP) classifiers (merging-based classification), homogenous (semantic) classes from overlapping database classes. The overlapping classes are detected using three measures in the proposed merging technique called dissimilarity, miss-classified ratio and accuracy. A supervised classification technique is realized using first two measures and unsupervised clustering is realized using the last one. In every level, previous level classes are merged by applying merging-based classification and splits it to several classes. In order to achieve more classes, this process is progressed. On a database consisting of 9100 medical X-ray images of 40 classes, evaluation of proposed technique is done.

Ramteke et al [17] implemented a technique to classify medical images automatically into two classes, namely, Abnormal and normal according to automatic abnormality detection and image features. Post-processing, classification, feature extraction and pre-processing are the major steps of this system. From abnormal and normal images, derived the statistical texture features. Images are classified using KNN classifier.

Performance of KNN classifier and kernel based SVM classifier (Linear and RBF) are compared. The KNN computes the confusion matrix and around 80% results can be obtained using KNN classifier, which is greater than SVM classification. So, images are classified using KNN algorithm. Abnormally classified images are post-processed for highlighting abnormal regions. Real CT scan brain images are used for experimentation.

Rajendran et al [18] implemted a technique to classify brain tumor in CT scan brain images. Hybrid-classifier, association rule mining, feature extraction and pre-processing are the major steps involved in this technique. Median filtering process is used for performing pre-processing and canny edge detection method is used for extracting edge features. Proposed a hybrid image mining technique using two techniques. The frequent pattern tree (FP-Tree) algorithm is used for generating frequent patterns from CT scan images, where association rules are mined.

For diagnosis, medical images are classified using decision tree technique. Highly accurate classification process is produced using this system. When compared with traditional image mining techniques, proposed method's efficiency is enhanced using the hybrid technique. Around 95% accuracy and 97% sensitivity results are produced on pre-diagnosed brain images database as indicated in experimentation results. For effective medical diagnosis, brain images are classified as malignant, benign and normal using this accurate decision tree classification phase by physicians.

Zhang et al [19] implemented a one-class kernel principle component analysis (KPCA) model based classification technique to classify medical images. The ensemble has one-class KPCA models which are trained using various image features of every image class. Product combining rule was proposed, which is used to combine KPCA models for producing classification confidence scores to assign images to every class.

A 3D optical coherence tomography (OCT) retinal image set and breast cancer biopsy image dataset is used for verifying proposed classification scheme's effectiveness. Complementary strength of this different feature extractors are exploited by various image feature combination. On two medical image set, promising results are obtained using this classification technique. On UCI breast cancer dataset also, this proposed technique is evaluated and obtained a competitive results.

Albarrak et al [20] supported the Three-Dimensional (3D) Optical Coherence Tomography (OCT) images analysis by using a proposed decomposition based technique which is coupled with local feature extraction for determining Age-related Macular Degeneration (AMD) presence in human eye's retina. In people aged over 50 years, vision loss is mainly caused by AMD. So, for AMD management, 3D OCT imaging technique is used as an indispensable diagnostic tool.

A given image is decomposed into sub-regions using recursive division of volume into sub-volumes. The extracted oriented gradient local binary pattern histograms for every sub-volume and feature vector is formed, classifier generation techniques are applied to it. A ten-fold cross validation is used for evaluating the proposed technique with 140 volumetric OCT images. With 94.4% Area Under the receiver operating Curve (AUC) value, better performance is exhibited using the proposed method.

Song et al [21] classified histopathology images using a transfer learning-based approach. At first, local features are Fisher Vector (FV) encoded for representing image features. The Convolutional Neural Network (CNN) model which are pretrained using ImageNet is utilized for extracting those local features. Pre-trained model is transferred to histopathology image dataset for the betterment and designed a new adaptation layer for further transforming FV descriptors to high discriminative power and classification accuracy. Malignant and benign class breast cancers are classified using publicly available BreaKHis image dataset and enhanced performance is achieved over state-of-the-art techniques.

Proposed Methodology

In this investigation, pre-trained CNN is used as a extractor of feature for extracting medical images multilayer convolutional features. Then, these features are encoded with discriminative feature score technique. After this, feature fusion process is carried out for classifying medical images with constructed feature representation. The proposed fusion feature strategy is implemented over pre-trained CNN model for fusing features with deep learning model. The detailed explanation regarding the proposed model is given in section below.

Discriminative Feature Score

The proposed model uses Fisher score as a key concept to develop this Discriminative Feature Score technique. The fisher score is a generic structural model that merges the advantages of discrminative and generative approaches. Based on this framework, image based matrix data are specified using vector as a process of kernel coding. This is considered as a key content for taking benefits over convolutional features that are extracted with CNN model. To enhance the scaling differences of images that comes under similar categories. Pyramid algorithm is utilized to improve scaling information of kernel coding and assists in constructing multi-scale discriminative score model.

Consider, I_i specifies input medical images, the multi-image set is generated using Gaussian Pyramid technique which is specified as $\{I_i^l\}_{l=0}^n$, where *'l'* is scaling level. Convolutional feature set $\{I_i^l\}_{l=0}^n$ on lth layer is specified accordingly. Consider, $X = \{I_i^l\}_{l=0}^n = \{x_1, \dots, x_T\} \epsilon R^D$ is set of multi-scale convolutional features, $\lambda = \{w_i, \mu_i, \sum_{i,} i = 1,2, \dots k\}$ be Gaussian mixture model based parameters fitting feature distribution from convolutional feature set where $w_i, \mu_i, \sum_i$ are number and weight, covariance matrix and mean vector; k is GMM component and M is a medical images count. This is considered for probability density function $p(x|\lambda)$ including parameters. Here, X is provided as gradient vector as in Eq. (1), Eq. (2) & Eq. (3):

$$G_\lambda^X = \frac{1}{T}\sum_{t=1}^T \nabla_\lambda \log p(x_t|\lambda) \quad (1)$$

$$p(x_t|\lambda) = \sum_{i=1}^k w_i p_i(x_t|\lambda) \quad (2)$$

$$p_i(x_t|\lambda) = \frac{\exp\{\frac{1}{2}(x_t-\mu_i)^T \sum_i^{-1}(x_t-\mu_i)\}}{(2\pi)^{\frac{D}{2}}|\sum_i|^{\frac{1}{2}}} \quad (3)$$

Based on existing score, g_λ^X of X is provided as in Eq. (4):

$$g_\lambda^x = F_\lambda^{-\frac{1}{2}} G_\lambda^x \quad (4)$$

Where F_λ is GMM information matrix. The mathematical derivation with mean and standard deviation is provided as in Eq. (5), Eq. (6) & Eq. (7):

$$g_{\mu,i}^X = \frac{1}{T\sqrt{w_i}}\sum_{t=1}^T \gamma_t(i)\left(\frac{x_t-\mu_i}{\sigma_i}\right) \quad (5)$$

$$g_{\sigma,i}^X = \frac{1}{T\sqrt{2wi}}\sum_{t=1}^T \gamma_t(i)\left[\left(\frac{x_t-\mu_i}{\sigma_i}\right)^2 - 1\right] (6)$$

$$\gamma_t(i) = \frac{w_i p_i(x_t|\lambda)}{\sum_{j=1}^K w_i p_j(x_t|\lambda)} \quad (7)$$

Where $\gamma_t(i)$ is probability of Gaussian component; σ_i is SD; $\sigma_i^2 = diag\,(\sum_i)$. It comprises of three gradients to mixture weight which are removed as it has information to provide for recognition task. Henceforth, gradients are used to construct fisher vector. As an outcome, linear vector specification of fisher score is specified as $\phi(X) = \{g_{\mu,1}^X, g_{\sigma,1}^X, \dots, g_{\sigma,K}^X\}^T$; where T is GMM component number. However, it is used to enhance performance of classification task. It is applied in every $\phi(X)$ as in Eq. (8):

$$f(z) = sign\,(z)|z|^\alpha \quad (8)$$

Where, $0 \leq \propto \leq 1$ is normalization parameter and set as 0.5. L_2 normalization is done for $\phi(X)$.

Fusion Strategy

To use every convolutional layer's hidden information that may assist in enhancing feature representation quality for medical images, convolutional features of medical images are extracted from convolutional layer and encoded with discriminative feature score in feature vector. However, direct outcomes of fully connected layers are considered as feature representation specifically for spatial features of medical images. As an outcome, there are numerous feature vectors that shows huge dimensionality vectors to construct input medical images final feature representation. Integrating those high dimensional features to single feature vector is highly needed. Moreover, still it is considered to be a confront task in fusing two or more vectors in large dimensional space owing to sparse features and diverse dimensionality. Moreover, integrated features large dimensionality may provoke dimensionality curse or over-fitting crisis. Therefore, it leads to lesser accuracy in classification. Henceforth, it is an appropriate choice to integrate large-dimensional features in low dimensional space. Subsequently, high dimensional features may be mapped into low

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dimensional feature space with sub-space learning technique.

For sub-space learning, supervised and un-supervised learning can be improved accordingly. However, these supervised learning techniques are prone to over-fitting problems specifically for tasks with lesser training samples. However, unsupervised techniques may preserve certain intrinsic methods of original data in lower-dimensionality feature space.

Here, this work anticipates an effectual rule to merge reduced feature vectors that maps along with unsupervised or supervised techniques respectively. With given input dataset, X_1 is considered as a discriminative vector of fully connected layers. It is mapped into lower dimensionality feature space with mapping of coefficient matrix as in Eq. (9), Eq. (10):

$$c = \theta^T X_1 \qquad (9)$$

$$\theta = \varphi\theta_s + (1-\varphi)\theta_u \qquad (10)$$

Where $X_f$is reduced feature, θ is matrix coefficient and θ_s and θ_u are achieved as learning methods. $\varphi$is scale factor to manage significance of mapping coefficient matrices.

CNN based Classification

With a pre-trianed CNN model and medical image dataset, the most crucial approach is constructing medical image's feature representations for performing classification. Based on the above model, this work constructs an integrated feature vector of medical images over fully connected layer or convolutional layer. Based on input data's special abstraction for all layers, from diverse fully connected or convolutional layers, features are extracted and are more essential for enhancing discriminative feature extraction.

Henceforth, it is an essential approach to construct feature score in multiple layers by stacking features integrated from multiple layers. A multi-scale improved discriminative feature score is used for constructing feature vectors over convolutional layers and specified as image based feature representation over convolutional layers. However, direct FC layer outputs are considered as image representation of FC layers. Then, every feature representations of diverse layers may include FC and convolutional layers which may be integrated with feature fusion model. This is alike of linear SVM based classification.

Here, pre-trained CNN model is used to design medical image classification task and it is employed to design input image's feature representation with appropriate structural information from diverse CNN architectural model. There is a clear distinctions towards CNN model as diverse network architecture and model parameters. Therefore, diverse CNN based on feature representations have certain information for diverse categories. The feature representation of CNN model with single CNN model is superior for extending fusion framework by stacking diverse feature representation of CNN models. The fused features are stacked with feature representation for medical image classification process.

Experimental Results

In this investigation, high resolutions medical images are utilized for computing anticipated model. In this work, a series of experiments are designed for verifying proposed classification method's effectiveness on benchmark medical image dataset named as HIS2828 dataset. Thus the simulation implements the coding network for extracting high level features in discriminative feature score technique. Traditional features are extracted and pre-trained convolutional neural networks are implemented using matlab toolbox.

Here, the performance of anticipated feature extractor and fusion strategies for medical image classification has been investigated. For making appropriate comparison of diverse pre-trained CNN models, this work reports average accuracy and computation time required for proposed model with pre-trained CNN model. Here, 70% samples are used in training and 30% is used in testing. Table I depicts proposed model's performance measure using fusion strategy.

Table I. Performance Metrics

S.No	Pre-trained CNN model	Accuracy	Running Time (%)
1	VGG-VD19	97%	15222
2	VGG-VD16	98.5%	14350
3	VGG-F	97.9%	4240
4	VGG-S	98%	7560
5	VGG-M	98%	8000
6	CaffeNet	98%	5050
7	AlexNet	98.2%	5320
8	Fused CNN	98.5%	4200

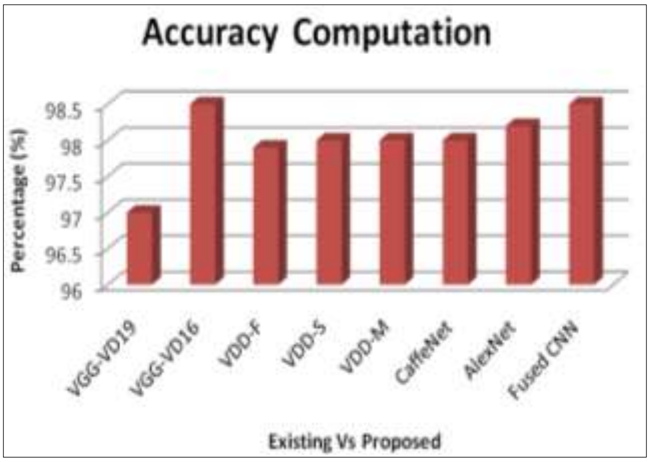

Fig. 1. Accuracy

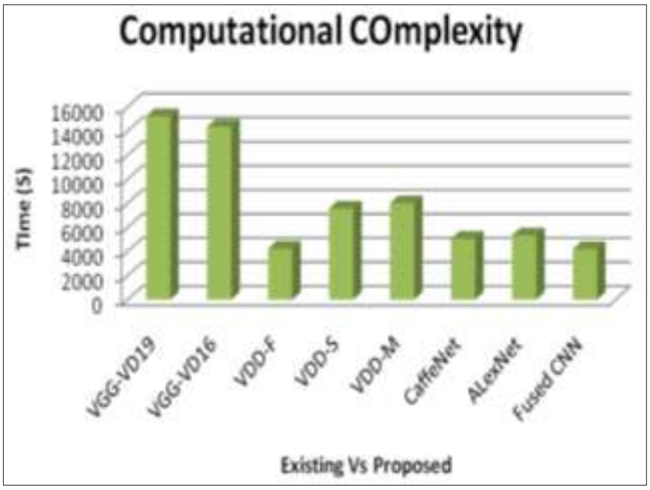

Fig. 2. Computational Complexity

The proposed model also computes computational time with diverse CNN models. It is known that the network model gives significant influence towards time consuming techniques. However, computational complexity concentrates on extracting convolutional features and modelling feature specifications. The complexity of proposed model is extremely lesser than the existing approaches as shown in figure 2. It shows acceptable efficiency to evaluate image classification within lesser hours using CNN method. By evaluating the performance of proposed model from convolutional as well as fully connected layers by fine-tuned pre-trained models. Technique of fusing pre-trained features are also attained for superior results. The outcomes may shows that convolutional features are most essential to model medical image's feature representation. From here, highly discriminative features are extracted from convolutional layers than FC layers using pre-trained CNN models.

The proposed model's accuracy is also higher while using fusion strategy while comparing it with features of fine-tuned models as shown in figure 1. There is some acceptable form for improvement based on fused features. However, pre-trained CNN models are enhanced by using fine-tunes strategies. Henceforth, classification accuracy attained from fined tuned model is superior than results of fully connected features of pre-trained model. The optimized parameters of pre-trained CNN models may enhance performance of provided task. Thus, it is not valid for some models like VGG-F. It is required for computing feature extraction ability using CNN.

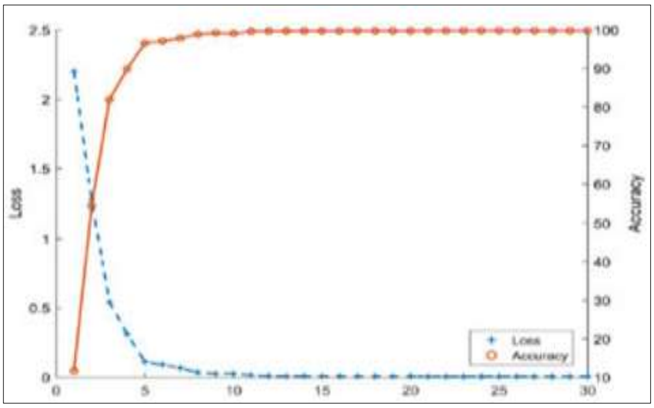

Fig. 3. Performance Validation

Ranking criteria is considered here to compute the significance of every feature vectors. For multi-class problem, there are n(n-1)/2. It is known that pre-trained CNN model may shows higher influence towards feature significance of every layer in medical image classification as shown in figure 3. For convolutional layer, features from first layers are relatively higher than convolutional layers. Similarly, features of fully connected layers are higher than other layers. It is extremely complex to complex to identify the significance of layers over the CNN model for extracting features based on evaluation results. Practically, the significance may changes over time. As well, features of convolutional layers shows drastic features in classification. It shows that the fused features from various layers is effectual to enhance feature representation ability for classification.

Conclusion

A new medical image classification algorithm is presented in this research work, that uses a pre-trained CNN as a feature extractor for extracting medical image's multi-layer convolutional features. Then, these convolutional features are encoded with discriminative feature score technique. The fusion strategy of feature discriminative feature score with pre-trianed CNN model to evaluate accuracy and computational complexity. The proposed model shows better trade off in contrary to existing approaches. In future, this work can be extended with the use of optimizer to attain global outcomes.

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