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A Deep Learning Framework With Optimizations For Automatic Detection And Localization Of Dendritic Spine

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With the emergence of Artificial Intelligence (AI), various problems in healthcare industry are being solved. Dendritic spines are protrusions that occur on dendrites of neurons reflecting indications pertaining to brain functionality. Therefore, dendritic spine detection research assumes significance in healthcare domain. There are many existing efforts towards detecting the dendritic spines from medical images automatically. However, there is need for further optimization in detection process besides localization of dendritic spines. Towards this end, in this paper, we proposed a deep learning based framework which exploits multiple models for efficient detection of dendritic spines. The framework exploits VGG16 model for extracting features from given medical image. The features are further used by faster RCNN model which is the actual dendritic spine detection model. The faster RCNN model exploits region proposal network which could provide extracted region proposals that make the detection process easier and efficient. We proposed an algorithm known as Learning based Dendritic Spine Detection (LbDSD) which exploits deep learning models for efficient detection and localization of dendritic spines. Our empirical study with a benchmark dataset revealed that the proposed deep learning framework and underlying algorithm outperforms existing deep learning based methods with highest accuracy 94.87%.

Keywords: Dendritic Spine Detection, Deep Learning, Artificial Intelligence, Faster RCNN, VGG16

1. Introduction

Artificial Intelligence (AI) technology is making inroads into every possible domain to solve existing problems. AI is widely used in different application domains including health care.A tiny membranous projection, shown in Figure 1, that arises from a neuron's dendrite and usually receives input from a single axon at the synapse is known as a dendritic spine, or spine. In addition to helping to carry electrical information to the cell body of the neuron, dendritic spines store synaptic strength. A narrow neck joins the spine head to the dendritic shaft in the majority of spines, which have a bulbous head known as the spine head. A single neuron might have hundreds or thousands of spines on its dendrites. Spines may function to enhance the amount of potential connections between neurons in addition to provide an anatomical basis for memory storage and synaptic transmission. Additionally, it's been proposed that variations in neuronal activity positively impact spine formation.

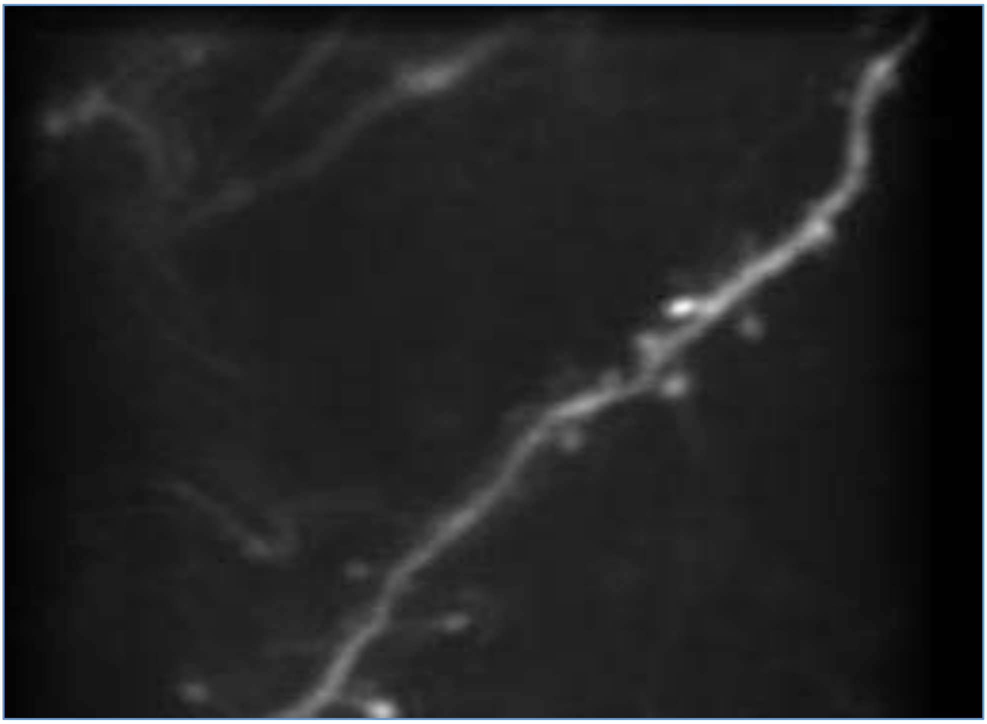

Figure 1: Florescence medical image showing dendrite and spines

There are many existing contributions pertaining to dendritic spine analysis. A deep learning system may identify cognitive impairment, indicating possible use in clinical and community-based settings for screening [6]. With low levels of Pb, Cd, and Hg have impaired memory due to disruptions in dendritic spine dynamics and cytoskeletal pathways [7]. Elevated glucocorticoid levels impair dendritic spines and microglia activation in mouse models, which worsen the course of Alzheimer's disease [11]. With the use of image analysis and patient-specific payment models, advances in AI and ML have the potential to completely transform orthopedic treatment [16]. Induced morphological changes are seen in dendritic spines, which are essential for synaptic plasticity. Spine modifications and disorders are frequently correlated [18]. Reduced neuroinflammation and maintaining dendritic spines, ultra-rapid FLASH mouse brain irradiation may have partially mitigated cognitive impairments [23]. In the human orbitofrontal cortex, severe stress dramatically lowers the density of mature mushroom spines, particularly in children [28]. From the review of literature, it is observed that deep learning models are efficient in medical image analysis. However, the detection of dendritic spines from microscopic images is difficult unless there is a hybrid approach in deep learning with an efficient pipeline.Our contributions in this paper are as follows.

1. We proposed a deep learning based framework that exploits VGG16 model for extracting features from given medical image and faster RCNN model for actual dendritic spine detection.
2. We proposed an algorithm known as Learning based Dendritic Spine Detection (LbDSD) which exploits deep learning models for efficient detection and localization of dendritic spines.
3. We developed a prototype to evaluate the proposed framework with hybrid tape learning approach towards automatic detection of dendritic spines.

The remainder of the paper is structured as follows. Section 2 reviews literature on prior works linked to dendritic spine analysis. Section 3 presents the proposed deep learning based framework and underlying models besides algorithm for automatic detection of dendritic spines. Section 4 presents our empirical study and results. Section 5 concludes our research findings and provides scope of the future research.

2. Related Work

The section reviews literature on prior works investigating on usage of deep learning models for automatic detection of dendritic spines. Luo et al. [1] emphasized how multiple synapse formation is facilitated by synaptic plasticity. High-resolution observation is made easier by new electromagnetic technology. The accuracy of the proposed classification approach. Chen et al. [2] approached outperforms the old ones in simultaneously detecting 3D crucial locations. Digital reconstruction of neural architecture is essential to neuroscience. Nourollah et al. [3] suggested DL approach expedites the compilation of training data while permitting imperfect annotations. Reaches a high level of segmentation and analysis accuracy. Tang et al. [4] suggested dendritic neural network (DNN) expands on the traditional paradigm and enhances task flexibility. Improved adaptability and a dropout mechanism guarantee encouraging results on a variety of datasets. Pei et al. [5] through increased neural activity and dendritic spine development, transcranial ultrasonography helps patients with vascular dementia remember things better.

Shi et al. [6] used ocular pictures, a deep learning system may identify cognitive impairment, indicating possible use in clinical and community-based settings for screening. Zhou et al. [7] observed that, with low levels of Pb, Cd, and Hg have impaired memory due to disruptions in dendritic spine dynamics and cytoskeletal pathways. Bland et al. [8] stated that, based on Fmr1 mouse models, higher dendritic spine density is the result of Fmr1 malfunction, which causes fragile X syndrome. Nader et al. [9] linked to brain plasticity are regulated by SRF. Adult neuron deletion modifies behavior, synaptic transmission, and spine shape. Huang et al. [10] explored and found that, for Alzheimer's disease are not very successful. In AD animal models, L-NBP has promise in possibly modifying synapse and spine degeneration.

Pedrazzoli et al. [11] elevated glucocorticoid levels impair dendritic spines and microglia activation in mouse models, which worsen the course of Alzheimer's disease. Wang et al. [12] compared to SVM and CNN demonstrates the superiority of deep learning on big datasets. In image processing, picture categorization is essential. Tang et al. [13] suggested using the gbest-guided artificial bee colony (GABC) algorithm to optimize the evolutionary dendritic neuron model (EDNM). Hardware compatibility enhances classification accuracy, especially with large data. Jiang et al. [14] presented a deep learning framework for dividing nuclei and neural cell bodies in pictures captured by electron microscopes. Nisar et al. [15] examined the application of deep learning to healthcare, focusing on illnesses affecting different bodily systems. Applications, tools, techniques, datasets, difficulties, and possibilities are all covered.

Helm et al. [16] found that, with the use of image analysis and patient-specific payment models, advances in AI and ML have the potential to completely transform orthopedic treatment. But given the opacity of algorithms and any biases in the data, prudence is necessary. Sharma et al. [17] posed obstacles for research on dendritic spine morphology. An innovative 3D reconstruction approach achieves classification accuracy and improves detection accuracy. Chidambaram et al. [18] induced morphological changes are seen in dendritic spines, which are essential for synaptic plasticity. Spine modifications and disorders are frequently correlated. Suratkal et al. [19] advanced in genome editing and optics have improved our understanding of dendritic spine plasticity and its involvement in learning and memory. Tachibana et al. [20] impaired synaptic function through clasmatodendrosis, which is typified by astrocytic alterations with Influenza-associated encephalopathy (IAE). To comprehend its pathogenesis, more investigation is necessary.

Boros et al. [21] associated with decreased spine density and changes in the architecture of the dendritic spine, which affect neuronal connections and cognitive function. Zagrebelsky et al. [22] impacted by dendritic spines, which also control synaptic transmission. The brain's neurotrophic factor (BDNF) and its receptors affect the plasticity and structure of the spine. Simmons et al. [23] reduced neuroinflammation and maintaining dendritic spines, ultra-rapid FLASH mouse brain irradiation may have partially mitigated cognitive impairments. Zhang et al. [24] exposed to valproic acid (VPA) developed characteristics resembling autism through activation of the Notch system. Notch inhibition enhanced behavior and controlled dendritic spine development and autophagy, pointing to a possible autism therapy. Ma and Zuo [25] developed in imaging technology make it possible to see and control synaptic shape and function, exposing complex changes that occur in synapses throughout memory and learning.

Treccani et al. [26] administrated quickly corrects abnormalities in the dendritic spine, indicating the potential use of synaptic remodelling in depression therapy. Okabe et al. [27] identified nanoscale characteristics is made easier by new imaging techniques. Synaptic structure, plasticity, and function depend on the actin dynamics of dendritic spines. Kaul et al.

[28] found that, in the human orbitofrontal cortex, severe stress dramatically lowers the density of mature mushroom spines, particularly in children. Shi et al. [29] explored and said, treated with DAC, they develop chemobrain, which is linked to changes in cytokine levels, hippocampus activity, and dendritic spine loss. Sun et al. [30] found that, treated with thioacetamide-induced MHE showed abnormalities in motor learning related to excessive cortical spine pruning that were regulated by glucocorticoid pathways. From the review of literature, it is observed that deep learning models are efficient in medical image analysis. However, the detection of dendritic spines from microscopic images is difficult unless there is a hybrid approach in deep learning with an efficient pipeline.

3. Proposed Methodology

This section presents the proposed methodology including deep learning framework, hybrid deep learning model, proposed algorithm, evaluation methodology and dataset used in the empirical study.

3.1 Problem Definition

Provided a fluorescence microscopic image pertaining to human brain or neurology as input, developing a deep learning framework which can automatically detect and localize dendritic spines is the challenging problem considered.

3.2 Our Framework

We proposed a deep learning based framework, shown in Figure 2, which exploits hybrid deep learning models in a pipeline towards efficient detection and localization of dendritic spines. The proposed system is based on supervised learning process which includes training and testing phases. The rationale behind this is that, there are training samples or labelled data available for the research of dendritic spine analysis. The given dataset is subjected to preprocessing in order to improve the samples.. The preprocessing also includes data augmentation which increases diversity of each training sample. The data is appropriately divided into 80% for training and 20% for testing. We proposed a hybrid deep learning model based on VGG16 and faster RCNN models as illustrated in Figure 2. Our proposed hybrid deep learning model is trained with the labelled medical images.After the training, the hybrid deep learning model gains knowledge required for detection and localization of dendritic spines. The model is persisted for using it repeatedly whenever there is need for detection of dendritic spines. The framework is evaluated with a benchmark dataset comprising of fluorescence microscopic images.

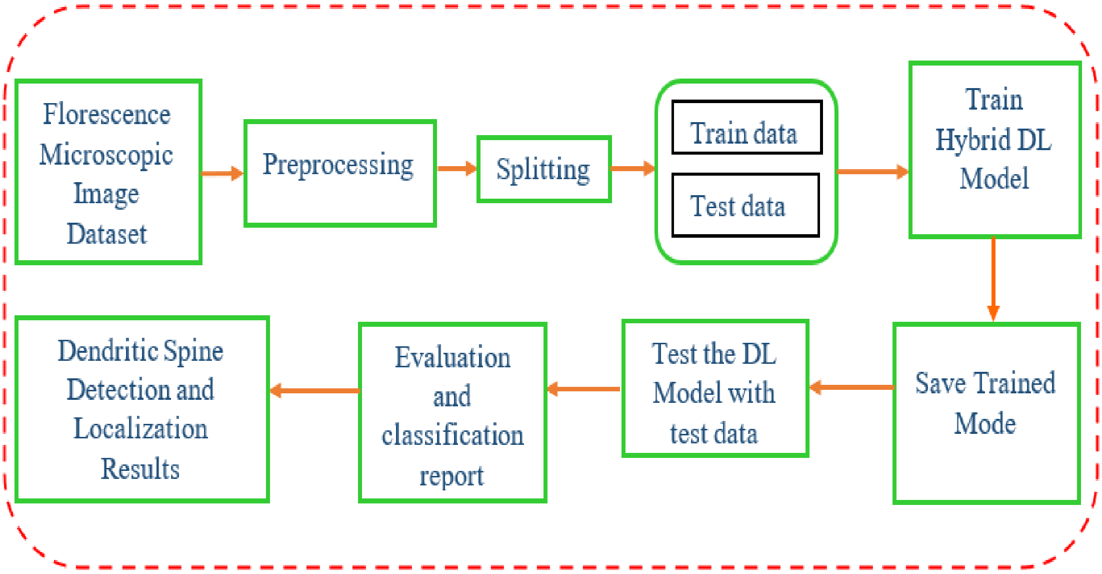

Figure 2: Proposed deep learning framework for dendritic spine detection and localization

The supervised learning process involved in the proposed framework depends on quality of training. It does mean that the model performance depends on the knowledge it gains from training data. Therefore, we improved the quality of training data with the help of data augmentation techniques in order to ensure diversity of each training sample. The framework is based on hybrid deep learning model which is designed to improve efficiency in the detection of dendriticspines. Our hybrid model has a pipeline of models including VGG16, faster RCNN along with Region Proposal Network (RPN).

3.3 Proposed Hybrid Deep Learning Network

Our deep learning model is a hybrid consisting of VGG16 model and faster RCNN model.The farmer is used to extract features efficiently from given medical image while the latter is meant for automatic detection and localization of dendritic spines in the given test image. The faster RCNN model comprises of Region Proposal Network (RPN) which is responsible to extract region proposals based on the inputs given by VGG16 model. In other words, the faster RCNN model exploits region proposals given by RPNfor automatically detection and localization of dendriticspines. The softmax andbounding box regressor associated with faster RCNN model help in detection of dendritic spines and localizing them respectively.

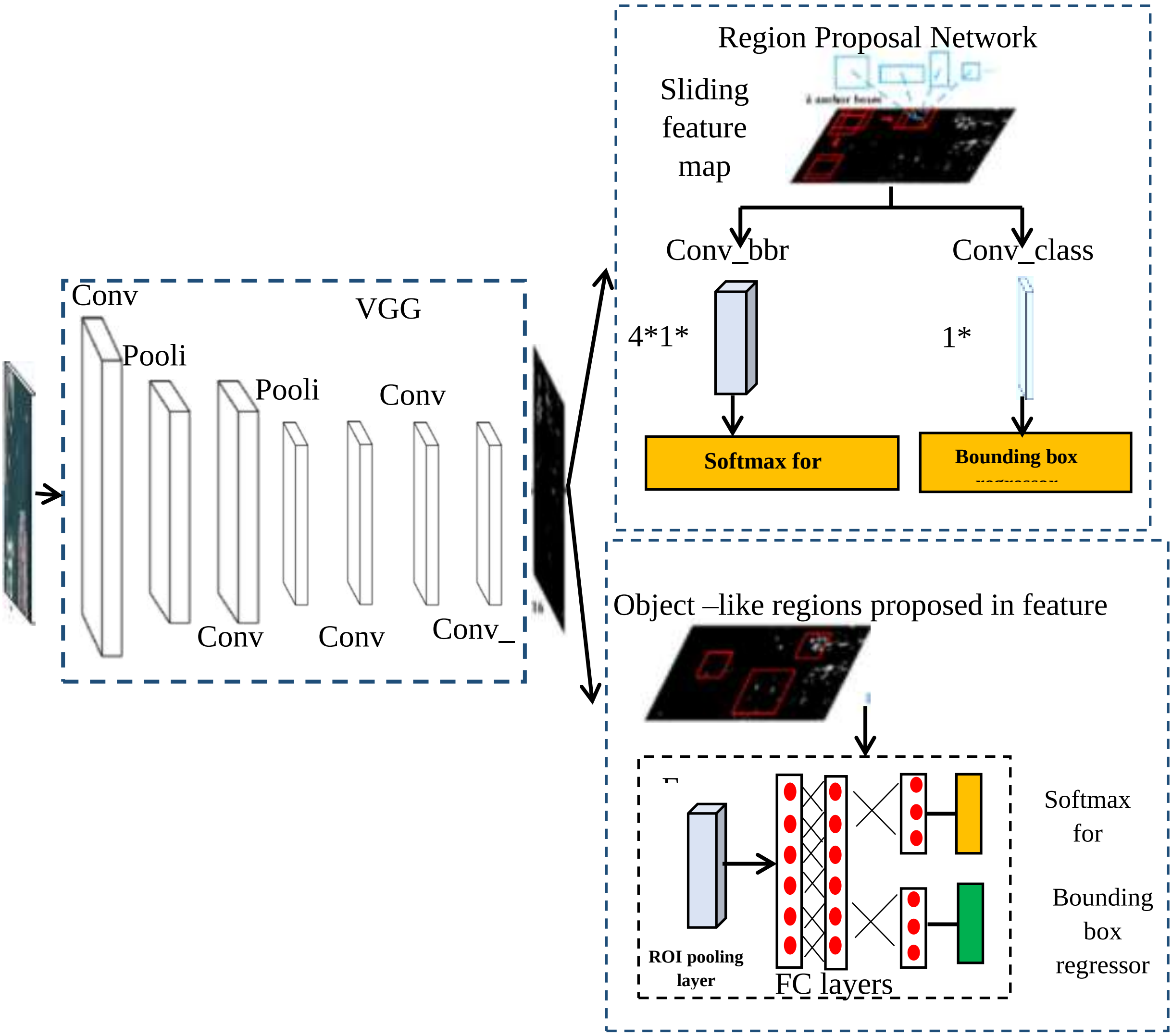

Figure 3: Proposed hybrid deep learning model

One of the most advanced object identification algorithms available now is Faster-RCNN [15]. The authors of this study, in an effort to improve upon their earlier work, Fast-RCNN, incorporate Region Proposal Networks (RPN) to speed up training and inference. The region ideas in the model's previous iteration [20] were not taught end to finish. During training, the detection and RPN pipelines were to share the weights of the feature mapper VGG-16 [22] layers. Used the IOU metric between the ground-truth bounding box and anchors as a filtering metric for each feature map cell of the VGG-16 to train the RPN model from scratch. Use the suggested areas from 1 to train the whole FasterRCNN after starting the detection pipeline with weights of VGG-16 trained on ImageNet [3]. Adjust the phase 2 VGG-16 weights and retrain the layers that are specifically connected to RPN. Retrain the whole Faster-RCNN model using the suggested layer. Throughout training, three loss functions are simultaneously optimized because the network as a whole has three output vectors. Categorical cross-entropyis used on the predicted items in the multi-classification output of the detection pipeline. Two coordinates—the object center (x, y) and the bounding box's height and breadth (h, w)—are included in the second output, a 4-element vector.

$$\mathrm{Loss}_{\mathrm{boundingBox}} = \sum_{\mathrm{i}\in\{\mathrm{x,y,w,h}\}} \mathrm{smooth}_{\mathrm{L1}}(\mathrm{i}_{\mathrm{pred}} - \mathrm{i}_{\mathrm{true}}) \qquad (1)$$

where

$$\mathrm{smooth}_{\mathrm{L1}}(\mathrm{x}) = \begin{Bmatrix} 0.5\mathrm{x}^2 \mathrm{if}\ |\mathrm{x}| < 1 \\ \mathrm{x}| - 0.5 \quad \mathrm{otherwise} \end{Bmatrix}$$

$$\mathrm{Loss}_{\mathrm{total}} = \mathrm{Loss}_{\mathrm{cls}} + \alpha\mathrm{Loss}_{\mathrm{boundingBox}} \qquad (2)$$

With one exceptionthat is, the RPN network classified each recommended region as either an object or a non-objectby using the same multi-class loss notion as in Eq. 2 and considering the suggested regions as the anticipated bounding boxes. With a fixed number of suggestions of 300 and an input picture size of 448 pixels by 448 pixels, horizontal flipping and otherswere utilized for data augmentation during training.

3.4 Dataset Details

Dataset comprising florescence medical images [31] are used in the empirical study. This dataset is widely used for dendritic spines analysis.

3.5 Proposed Algorithm

We proposed an algorithm known as Learning based Dendritic Spine Detection (LbDSD) which exploits deep learning models for efficient detection and localization of dendritic spines.

Algorithm: Learning based Dendritic Spine Detection (LbDSD)
Input: Dendritic spine analysis dataset D
Output: Dendritic spine detection results R, performance statistics P

1. Begin
2. D’←Preprocess(D)
3. (T1, T2)←DataSplit(D’)
4. Configure hybridDL model m (as in Figure 3)
5. Compile m
6. Train m using T1
7. Save m for future reuse
8. Load m
9. R←Test(m, T2)
10. P←Evaluate(R, ground truth)

11. Display R
12. Display P
13. End

Algorithm 1: Learning based Dendritic Spine Detection (LbDSD)

As presented in Algorithm 1, it takes dendritic spine analysis dataset as input, performs detection of dendritic spines and localizing them besides providing results in the form of dendritic spine detection and also performance statistics. The given dataset is subjected to preprocessing where the diversity of each sample is increased. The data is split into training set, denoted as T1, and test set, denoted as T2, respectively. A hybrid deep learning model is configured as illustrated in Figure 3, then it is compiled and subjected to training using the test data.Once the model is trained, it is persisted for future reuse. Model which has been saved is reloaded in order to perform dendritic spines detection and localization by using T2.The model is evaluated by comparing the ground truth values with the modal predictions.

3.6 Evaluation Methodology

Since we used learning based approach (supervised learning), metrics derived from confusion matrix, shown in Figure 4, are used for evaluation our methodology.

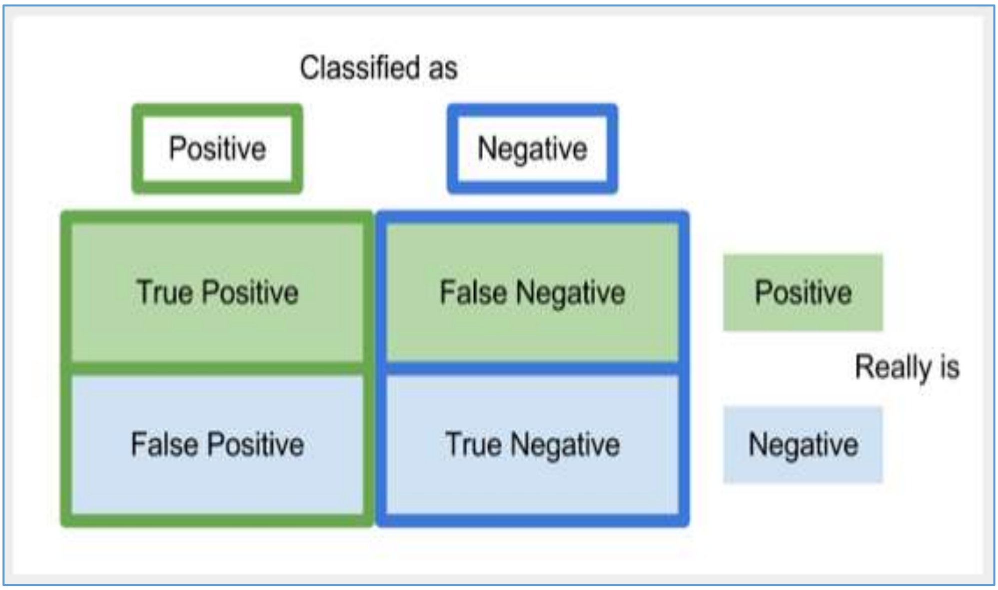

Figure 4: Confusion matrix

Based on confusion matrix, the predicted labels of our method are compared with ground truth to arrive at performance statistics. Eq. 3 to Eq. 6 express different metrics used in the performance evaluation.

$$\text{Precision (p)} = \frac{\text{TP}}{\text{TP+FP}} \quad (3)$$

$$\text{Recall (r)} = \frac{\text{TP}}{\text{TP+FN}} \quad (4)$$

$$\text{F1-score} = 2 * \frac{(\text{p} * \text{r})}{(\text{p+r})} \quad (5)$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (6)$$

The measures used for performance evaluation result in a value that lies between 0 and 1. These metrics are widely used in machine learning research.

4. Experimental Results

This section presents experimental results pertaining to medical image analysis towards automatic detection and localization of dendritic spines. The proposed deep learning framework and underlying hybrid deep learning model are evaluated for the performance in detection process. A benchmark dataset [31] comprising of fluorescence microscopic images are used for supervised learning process. The proposed deep learning model is evaluated and compared with existing models like baseline CNN and the faster RCNN models. The observations are made in terms of detection and localization of dendriticspines along with performance statistics.

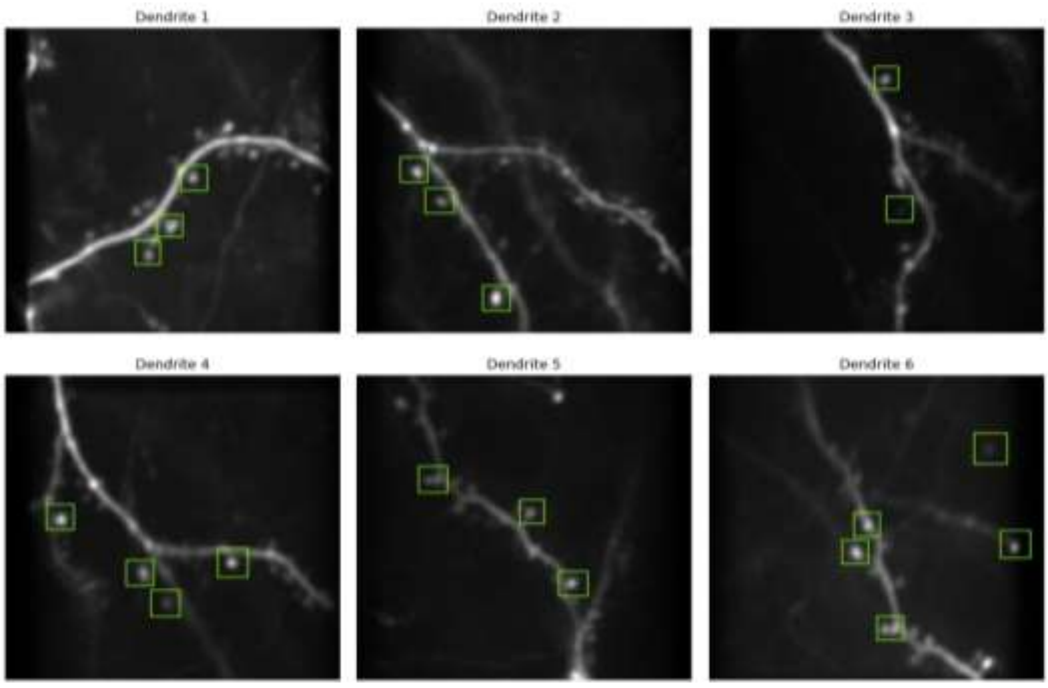

Figure 5: Results of dendritic spine detection and localization

As presented in Figure 5, it is observed that in each dendrite there are number of spines that are detected and also localized with the help of bounding boxes. The detection process is carried out by softmax layer while localization is carried out by bounded box regressor associated with faster RCNN model.

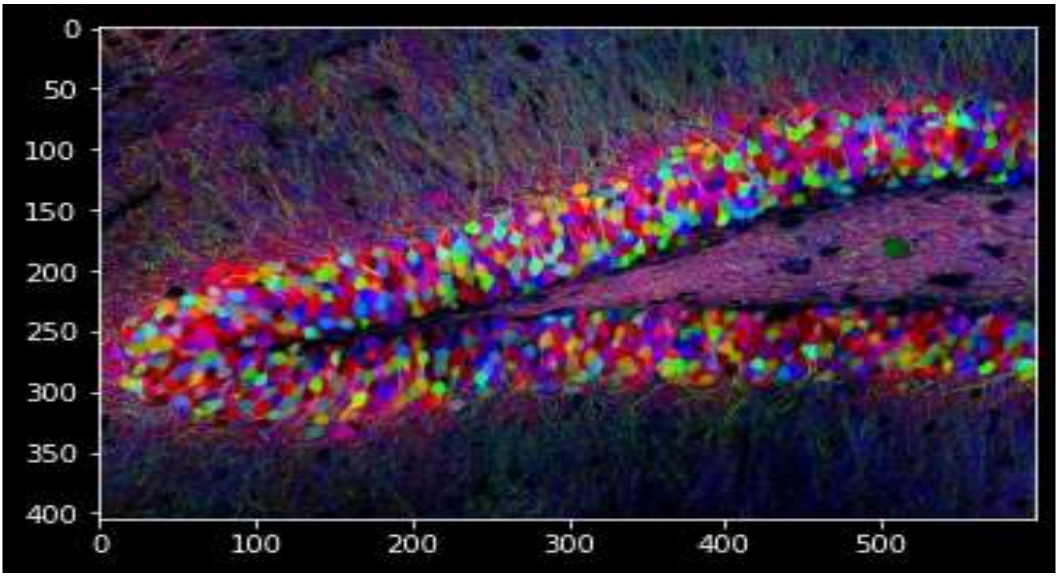

Figure 6: The result of K-means clustering

As presented in Figure 6, it visualizes the result of K-means clustering associated with enrich spines.

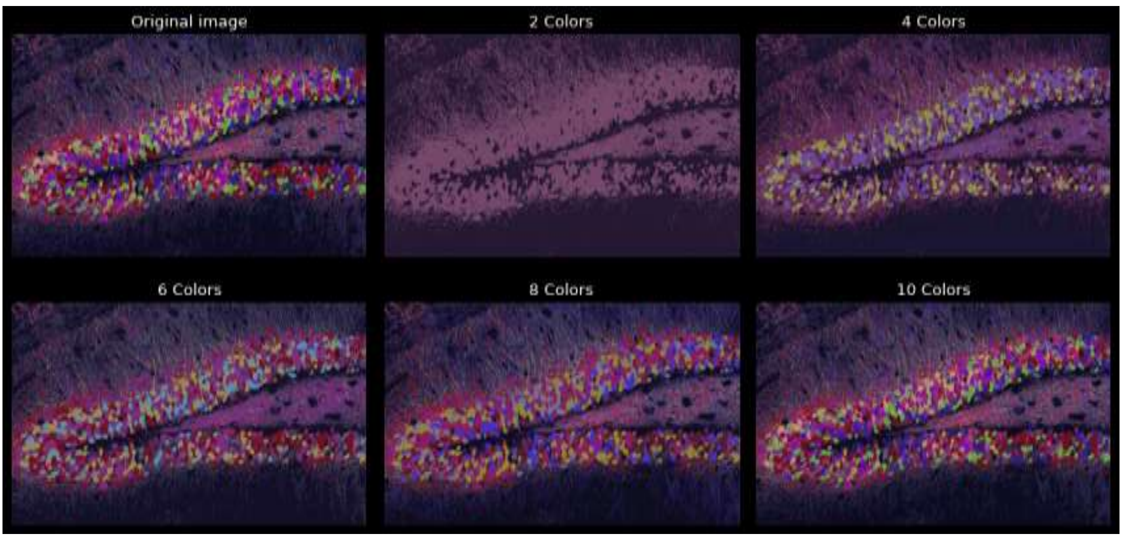

Figure 7: Results of clustering with different colors

As presented in Figure 7,the results of clustering process is visualized with original image followed by number of images with different number of colors.

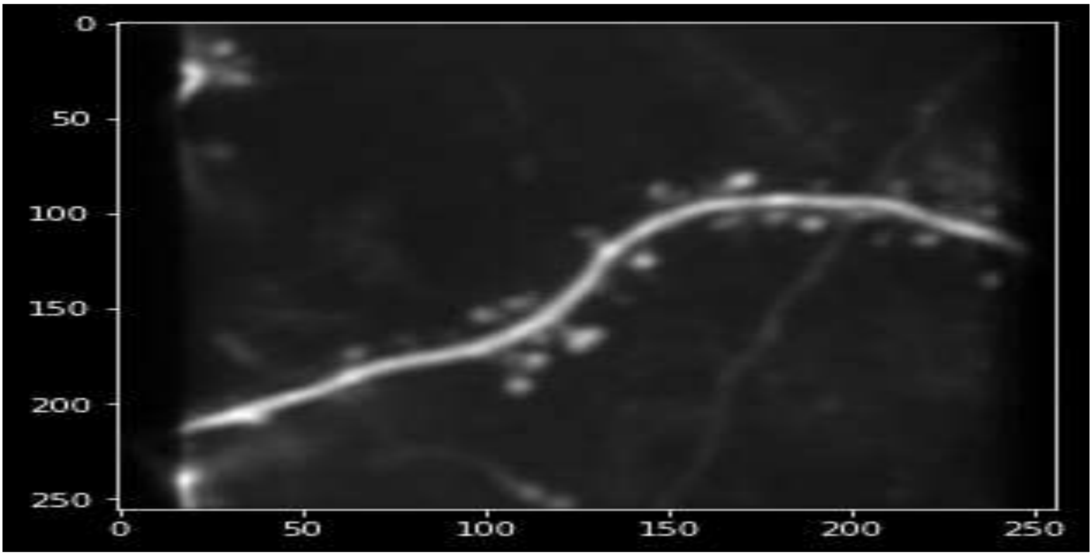

Figure 8: Shows an input image containing dendrite

As presented in figure 8, it is observed that the input image has clearly visible dendrite with many associated spines.

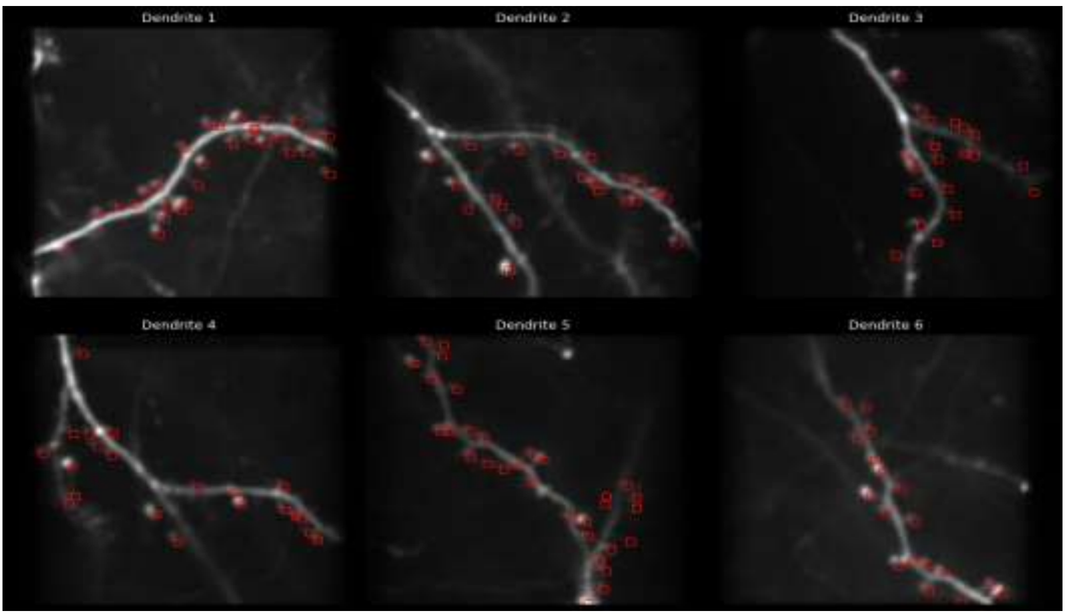

Figure 9: Shows results of another experiment with dendritic spine detection and localization

As presented in Figure 9, it is observed that there are number of dendrites and each dendrite has several spines associated with it. Results revealed that the proposed deep learning model is able to detect dendrites and also localize them.

	Precision	Recall	F1-Score	Accuracy
Baseline CNN	0.8964	0.8521	0.8736	0.9017
Faster RCNN	0.9456	0.8256	0.8815	0.9154
Hybrid Model (Proposed)	0.9274	0.9129	0.92	0.9487

Table 1: The results of experiments with different deep learning models

Results of experiments with the proposed hybrid deep learning model and existing deep learning models are provided in Table 1.

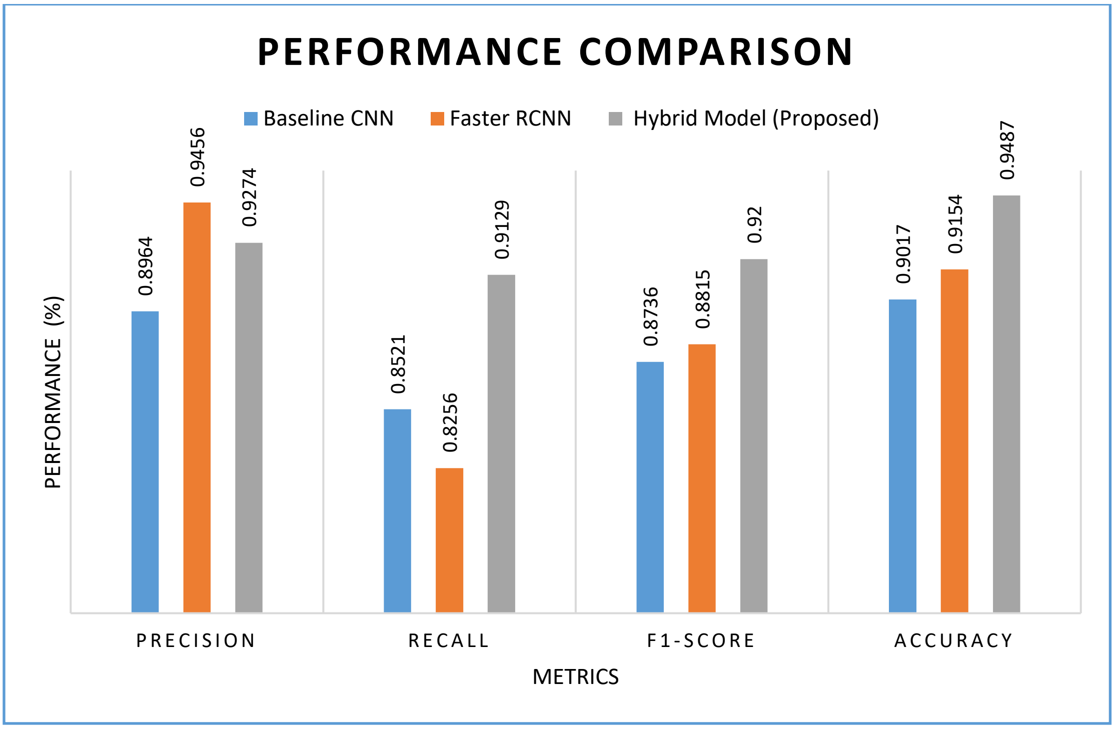

Figure 10: Performance comparison among deep learning models

As presented in Figure 10, it is observed that the proposed hybrid deep learning model is compared with two existing deep learning models like baseline CNN and faster RCNN. There are many observations in the empirical study.Each model exhibited different level of performance in detection and localization of dendriticspines. The baseline CNN model achieved 89.64% precision while faster RCNN showed 94.56% precision and the proposed hybrid model exhibited 92.74% precision. With respect to recall, the baseline CNN model achieved 85.21%, faster RCNN model 82.56% and proposed hybrid model 91.29%. With regard to F1-score, the baseline CNN model exhibited 87.36%, faster RCNN model achieved 88.15% and the proposed deep learning model could achieve 92% F1-score. When accuracy of the models is considered, the baseline CNN model achieved 90.17% accuracy, faster RCNN 91.54% and proposed hybrid model could achieve 94.87% accuracy. From the results, it is observed that the proposed hybrid deep learning model could achieve highest accuracy with 94.87%.

5. Discussion

This paper is aimed at developing a deep learning framework and algorithm for automatic detection of dendritic spines in the given medical image. The system is built in such a way that, it not only detects dendritic spines but also localizes them to help healthcare professionals making well informed decisions. This research will help healthcare professionals towards exploring the role of dendritic spines in brain related communications. As the dendritic spines are found dynamic in their size due to runtime communication dynamics of neurons,The proposed framework exploits VGG16 model for feature extraction and RPN for generating region proposals that simplify detection process. The faster RCNN model takes inputs from RPN in the form of region proposals and the automatically detects dendritic spines. The faster RCNN Model has provision for localizing dendriticspines once they are identified. The proposed deep learning based system is found efficient when evaluated with a benchmark dataset. The models involved in the framework are seamlessly integrated in a pipeline to achieve better performance in the dendritic spine detection. The proposed algorithm is capable of using all deep learning models towards automatic detection and localization of dendritic spines.

5.1 Limitations

The proposed system is capable of detecting and localizing dendritic spines. However, the system has certain limitations. The dataset used for training has limited number of samples and the generalization of findings is difficult. The system does not exploit hyperparameter optimization though it has potential to leverage performance of deep learning models. The proposed system is based on multiple deep learning models in a pipeline towards efficient detection of dendritic spines. But it could be improved further with Generative Adversarial Network (GAN) architecture that is well known for dealing with the problem of limited sized data.

6. Conclusion and Future Work

In this paper, we proposed a deep learning based framework which exploits multiple models for efficient detection of dendritic spines. Different deep learning models involve convolutional layers that are used as part of the framework towards extracting features from given image. The usage of multiple deep learning models in coordination and in a pipeline has its impact on improving dendritic spine detection process. The framework exploits VGG16 model for extracting features from given medical image. The features are further used by faster RCNN model which is the actual dendritic spine detection model. The faster RCNN model exploits region proposal network which could provide extracted region proposals that make the detection process easier and efficient. We proposed an algorithm known as Learning based Dendritic Spine Detection (LbDSD) which exploits deep learning models for efficient detection and localization of dendritic spines. Our empirical study with a benchmark dataset revealed that the proposed deep learning framework and underlying algorithm outperforms existing deep learning based methods with highest accuracy 94.87%. In future, we intend to enhance our deep learning framework by implementing a Generative Adversarial Network (GAN) architecture towards more efficient detection and localization of dendritic spines.

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