A Transfer Learning Based Approach for Sunspot Detection

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Abstract. Realtime space weather activity tracking has improved over the years advancements in astronomy research due to recent instrumentation techniques. Sunspots are important phenomenon of sun and are visible on photosphere of sun surface. The occurrences of sunspots determine overall solar activities, sunspots are being observed from early eighteenth century. In this study, we have implemented a DL model which automatically detects sunspots from HMI image datasets. A DL based VGG16 model is used for deep hierarchical features extraction and passed to softmax layer for classification. The proposed DL approach achieved improved classification results and model has shown the good performance with HMI imaging data which is equal to 97.8%, 96.25% 100%, 98%, and 93.37% for accuracy, precision, recall, F-score and specificity respectively. The proposed DL based model has achieved improved results and robust performance solar spot recognition system to monitor solar activities.

Keywords: Sunspot, Deep Learning, CNN and Transfer Learning.

1 Introduction

Sun considered to be the core research object of astrophysics from 17^{th} century[1], conventionally Sunspot observation was carried out by drawing and also included location, sunspot number, and area of the sunspots[2] . In recent days solar physics in conjunction with machine learning, Computer vision and deep learning techniques has showed various developments like event detection like coronal hole, sunspot, prominence, solar flares [3][4]. In the recent days DNN algorithms outperformed the tasks of classification and detection[5]. There are various studies multidisciplinary approaches addressed in the filed of Microscopic imaging[6][7], Medical imaging[8][9][10][11], CAD based systems[12][13] and anomaly detection[8][14][15]. Solar activates plays an important role in determining the efficient observation of space weather. Sunspots are visualized as dark patches on solar photosphere due variation in surface temperature, sunspots[16] appearance is dynamic in nature and turns out be a challenging task for differentiating among sunspots and group of sunspots manual visualization requires experience human expertise and deep learning based approaches could impact to enhance the decision making systems for better understanding the solar.

In recent days there has been improvement in studies of solar exploration with increased number of space missions and improved instrumentation technologies which lead researchers with large amount of solar activity data[17]. Many researchers with the help of deep learning techniques has introduced various methods to detect the sunspots[18][19][20], filament recognition [21], flare detection[22][23][24], and sunspot groups[25][26] various object of interests for observing the solar activities.

In recent works Deep Convolution Neural Networks (DCNN) has gained focus in solar physics for sun activity tracking, DCNN algorithms for the task of image classification and detection in the field of computer vision gained popularity and input is images with labels. The proposed work consists of SDO data sources. Sunspot and quite sun images can be seen in figure 1 provided by NASA SDO [1] mission database repository.

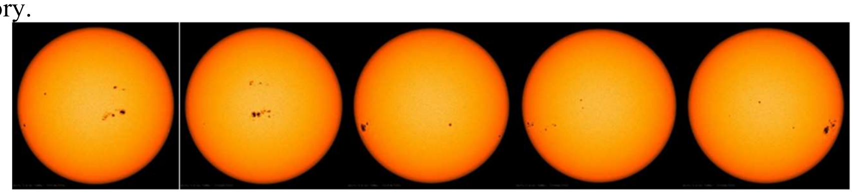

Fig. 1. Sunspot images

The paper organized as follows. In section 2. We discuss the previous works with deep learning and machine learning methods applied to understand the solar activity tracking and classification. In section 3. We address the Proposed model for addressing sunspot detection. In section 4. We present experimental analysis and discussion and finally, in section 5. Conclusion of the proposed model.

2 Related work

The improved instrumentation led to exponential generation of data such as image data, spectral data and time series data in the field of Astronomy[27]. In recent days the

[1] https://sdo.gsfc.nasa.gov/data/

large quantum of data generated by space and ground based observatories, existing data quantity has attracted and initiated multidisciplinary research.

The image processing terminology was introduced for sunspot detection by Colak & Qahwaji [28], Magnetogram and MDI intensitygram images these images are the indicators of magnetic fields visible in the photosphere of sun, image processing technique has used to detect the sunspot and sunspot groups with the accuracy of 99% and 92% respectively [28][29]. In [30], detection of sunspot with morphological approaches with adoptive threshold based methods with 95% recognition rate on Huairou Solar Observing Station (HSOS) full-disk vector magnetic field images. Next, In [31], Ruben du Toit et al. addressed the task of sunspot detection and tracking with OpenCV library with edge detection and scale-invariant features for localization of sunspot, tracking is followed by Discriminative Correlation Filter with Channel and Spatial Reliability method and Kernelized Correlation Filters were employed for tracking with Michelson Doppler images as input for the proposed approach.

Deep Convolution Neural Networks(DCNN) methods are most widely used in recent days for tracking and sun activities such as sunspot detection[20], Solar flare Prediction [24][32], ribbons[33], coronal holes[4] and Prominences[4]. In continuation various approaches for solar event detection and classification. Pandey et al. in [24], deep learning based solar flare prediction with DCNN based approach with Full-disk magnetogram images from Helioseismic and Magnetic Imager (HMI) onboard Solar Dynamics Observatory (SDO) were used for flare prediction as binary and multiclass classification with AlexNet, VGG16 and ResNet34 as base architecture for feature extraction. Evaluation performance is done by True Skill Statistics(TSS) with 0.47 and 0.55 for binary classification, for multi-class classification as 0.36, and Heidke Skill Score(HSS) is noted as for Binary classification 0.46 and 0.43 and Multiclass scenario 0.31 scores with alexnet employed feature extraction. In [32], they proposed solar flare prediction is done with Transfer Learning Alexnet based architecture with adaptive average pooling and log softmax is used for classification of flares. The performance of the proposed model is evaluated with TSS and HSS with datatype as augmentation, oversampling, and normal datasets, noted that TSS is 0.47 with oversampling, 0.44 with data augmentation, 0.63 with normal dataset, and HSS is 0.35 for oversampling, 0.37 with data augmentation, 0.62 with normal dataset. Love et al. in [33], Solar flare observations with CNN based approach with AiA 1,600° images were used to detect flare ribbon observations and were able to achieve overall accuracy of 94% with the K-fold validation technique. He et al. in [25], addressed the sunspot group classification with HMI and MDI Magnetogram with DCNN based CornerNet-Sac-cade method is employed for the detection of sunspot group with Mount Wilson Magnetic Classification. The proposed work noted that results with performance metrics as Accuracy(94%), Recall(93%), AP(90%) and Precision(94%). Solar activity monitoring tasks can be eased and can be improved with computer vision techniques.

3 Proposed Methodology

The proposed work deals with the classification of sunspot images into sunspot or quite sun. Transfer learning methods are adopted with VGG16 as base architecture. The input images were RGB channel with resized to standard size of VGG16.

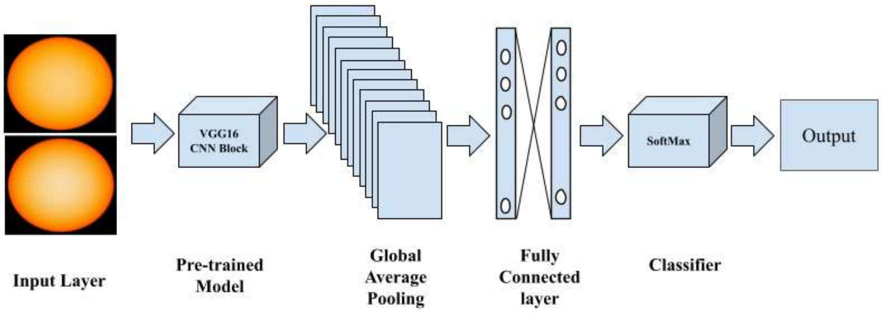

Fig. 2. DCNN based model for classification of sunspot;

3.1 Dataset Preparation

Solar Dynamics Observatory (SDO) Helioseismic and Magnetic Imager (HMI) images were considered. The images used for experimentation are publicly available and retrieved from NASA SDO [34][20]. All images in this database are resized a fixed size of 224x224 pixels. And dataset split into Training, Testing and validation.

3.2 Proposed Architecture

DCNN approach employed to tackle task of sunspot classification with Transfer Learning based model with VGG16 [35] as base architecture. Deep features extracted by the input SDO images passed to softmax for prediction.

In this study we present deep learning based on CNN is used for the classification of sun images into quite sun or sunspot. Features are generated by raw input images hierarchically based on the depth of the model.

Convolution Neural Networks are imitation of the cerebral cortex of human brain large training amount datasets requires for training a complex model. Features are extracted with operations like filtering, normalization and nonlinear activation operation and learning of algorithm is carried out with backpropagation algorithm and gradient descent optimization algorithms.

Deep Convolution neural network is stack of Input layer, convolution layer, Pooling layer, fully connected layer and output layers. These layers are building block of any deep convolution architecture. In context of image processing feed forward process is adopted for feature extraction, Convolution layer consists of multiple convolution filters of similar size to extract feature. Every filter is matrix of two-dimension with corresponding weights, the value of every neuron for present convolution layer is the result obtained by multiplication of data of previous layer with the convolution filter, and the addition of corresponding offset. The feature extraction involves the sequential scan of filter on input data of upper layer according to feature stride factors. Here Input image of size a*b passed through input layer to convolution block, convoluting with given kernel size x*y gives output known as *feature map*, later non linearity added to the network like Relu, ELU, sigmoid, tanh and LeakyRelu most commonly used functions.

$$C_{ab} = \sigma(\sum_{xy} w_{xy} v_{(a+x)(b+y)} + B) \tag{1}$$

Where C_{ab} referred as unit in feature map at location (*x; y*), σ represents the activation function. w_{xy} is weights of kernel $v_{(a+x)(b+y)}$ designates an input unit at location $(a+x, b+y)$, and B is bias of feature map.

Activation function considered is ReLU in general form its shown as equation (**) here any negative values is mapped to 0 and rest values no change.

$$f(r) = \max(o, r) \tag{2}$$

The ReLU hyperparameter saturates for negative inputs.

Pooling is most important operation in terms of reducing feature map dimension and overfitting of model, Pooling layer also called as down sampling. There are few pooling operations namely Max pooling and average pooling layers. Here the key concept is to reduce the size by mapping the values based on application or object pixel distribution. Stride factor can be used as pixel shifts over the input matrix. Padding can be used to add pixels which helps to keep width and height of previous layer. When we consider max pooling, it covers the most active feature from the pooling region which implies that it could be generalized for collecting texture information and Average pooling is responsible for background information preservation due to consideration of all features of the pooling region. Hyper parameters in pooling layers are Filter size and stride. Pooling layer represented as $w \times h \times d$ which is width, height and depth and with kernel size as f and stride as s the pooling computed as $w_p \times h_p \times d_p$ represents width, height and depth after the pooling.

$$w_p = (w - f) / s + 1 \tag{3}$$

$$h_p = (h - f) / s + 1 \tag{4}$$

$$d_p = d \tag{5}$$

After the extraction of local features from convolution layer. Fully connected layer applied to enhance the nonlinear mapping, perceiving of global information and aggregation local features to perform classification. Each neuron in the l layer is connected to $l+1$ layer. The formula for fully connected layer is

$$y_i^{(l)} = f(\sum_{i=1}^{n} x_i^{(l-1)} * w_{ji}^{(l)} + b^{(l)}) \tag{6}$$

Where n is no of neurons in the previous layer, l is the present layer, $w_{ji}^{(l)}$ is the connecting weight of neurons j in present layer and neurons i in the previous layer, $b^{(l)}$ is the bias of j neuron and f as activation function.

The final output layers derived from fully connected layers which are located at the end of convolution blocks, output layer fed input from previous these layers take the output from the hidden layers and process it such that for each data file a pre-defined class is predicted by the network. Classification probability. The classification probability of the image is calculated by the CNN's softmax layer, which is formulated as follows:

$$p(x_i) = \frac{e^{x_i}}{\sum_{K=1}^{K} e^{x_k}} \tag{7}$$

where x_i represents the output of the fully connected layer for class i, K is the total number of classification categories, and p represents the classification probability the outputs from multiple neurons mapped to (0,1) interval. SoftMax outcome will be classification probability for each category and assigns the maximum classification probability value and corresponding category as the final outputs.

3.3 Performance Evaluation

The proposed sunspot prediction model with binary classification strategy to classify input data as Sunspot or Quiet sun via DCNN model. Performance evaluation is carried out with Accuracy, Precision, Recall, F-measure and Specificity are expressed in following equations 8-12.

$$\text{Precision} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{8}$$

$$\text{AZ} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{TN} + \text{FP}} \tag{9}$$

$$\text{F1} - \text{score} = \frac{2 \cdot \text{TP}}{2 \cdot \text{TP} + \text{FP} + \text{FN}} \tag{10}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{11}$$

$$\text{SE} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{12}$$

Where TP, TN, FP, and FN were defined to represent the number of true positive, true negative, false positive, and false negative respectively.

4 Results and Discussion

The proposed work deals with the classification of sunspot images into sunspot or quite sun with the help of 5fold cross validation technique is used to identify the sunspot.

Table 1. Results.

	Accuracy	Precision	Recall	F-measure	Specificity
1st fold	100	100	100	100	100
2nd fold	97.83	95.84	100	97.87	95.6
3rd fold	100	100	100	100	100
4th fold	99.71	100	100	100	88.4
5th fold	91.46	85.43	100	92.14	82.89
Average	97.80	96.254	100	98.00	93.37

Table 1 present classification models to classify sunspot were evaluated on a completely new unseen testing dataset. The data has been collected from different resources. The training dataset, as described in section 1. The performances of the proposed models in terms of accuracy, F1 score, precision, and recall. From the table 1, we can see that the proposed model has got good result using VGG16 model achieved good results with respect to all evaluation metrics.

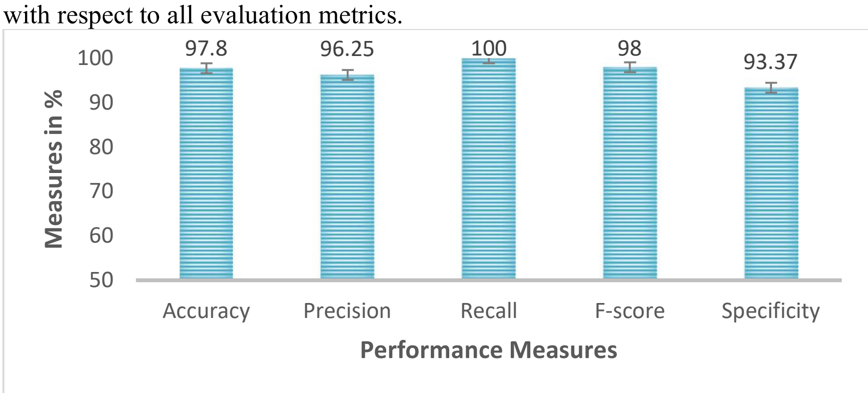

Fig. 3. Performance measures for sunspot classification

The proposed DL approach achieved improved classification results and model has shown the improved results with HMI data set which is equal to 97.8%, 96.25% 100%, 98%, and 93.37% for accuracy, precision, recall, F-score and specificity respectively.

5 Conclusions

Sunspots are known as key object of astrophysics and sunspots are the most prominent feature for assessing space weather and are located in solar photosphere. In this work, we have implemented a deep learning model which automatically detects sunspots from HMI image datasets. Data divided into training, testing and validation subset and passed to classification pipeline. The proposed work focus classification of sunspot via DCNN based approaches has shown average of 97.8% of overall accuracy K-fold cross validation method. The performance is evaluated with Accuracy, Recall, Precision, F-measure and specificity. Based on the experimental setup we conclude that proposed DCNN based model efficient to classify the HMI images into sunspot or quite sun. Realtime detection and tracking could be addressed as future work with the help of various object tracking algorithms.

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