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Skin Cancer Classification using Convolutional Capsule Network (CapsNet)

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Researchers are proficient in preprocessing skin images but fail in identifying efficient classifiers for classifying skin cancer due to the complex variety of lesion sizes, colors, and shapes. As such, no single classifier is sufficient for classifying skin cancer legions. Convolutional Neural Networks (CNNs) have played an important role in deep learning, as CNNs have proven successful in classification tasks across many fields. However, present day models available for skin cancer classification suffer from not taking important spatial relations between features into consideration. They classify effectively only if certain features are present in the test data, ignoring their relative spatial relation with each other, which results in false negatives. They also lack rotational invariance, meaning that the same legion viewed at different angles may be assigned to different classes, leading to false positives. The Capsule Network (CapsNet) is designed to overcome the above-mentioned problems. Capsule Networks use modules or capsules other than pooling as an alternative to translational invariance. The Capsule Network uses layer-based squashing and dynamic routing. It uses vector-output capsules and max-pooling with routing by agreement, unlike scale-output feature detectors of traditional CNNs. All of which assist in avoiding false positives and false negatives. The Capsule Network architecture is created with many convolution layers and one capsule layer as the final layer. Hence, in the proposed work, skin cancer classification is performed based on CapsNet architecture which can work well with high dimensional hyperspectral images of skin.

Keywords: Capsule Network, CNN, Computer Aided Diagnosis, Skin Cancer Classification, Skin Cancer Detection

Introduction

Skin cancer is one of the most common cancers all over the world. It is estimated that approximately 9,500 people in the U.S. are diagnosed with skin cancer everyday.[1] There are 5.4 million new cases of skin cancer in the United States every year[2], and according to the current estimation, one in five Americans will develop skin cancer in their lifetime. Like the other types of cancers, most skin cancers can be cured if diagnosed early enough. Skin cancer is primarily diagnosed visually, beginning with an initial clinical screening, followed by dermoscopic analysis, and ultimately a biopsy and histopathological examination. The biopsy method is done by removing or scraping off a skin sample that will undergo a series of laboratory testing, which can be painful and time consuming. Dermoscopy is one of the golden techniques to exam skin lesions because it can capture high-resolution images of the skin regardless of interruption from surface reflections.[2] Experienced clinicians use this high-resolution imaging to evaluate the possibility of melanoma at the early stage with considerable accuracy. Unfortunately, there are not enough experienced dermatologists all over the world. To solve the problems specified above, computer-aided diagnosis is performed to classify different skin associated diseases using dermoscopy images. However, over the last decade, the conditions for developing computer-aided skin legion diagnosis systems were unfavorable. For instance, the numbers of cases in the database were inadequate for learning accuracy and for extracting useful features. Moreover, dermoscopic images are acquired via a specialized instrument, and histological images are acquired via invasive biopsy and microscopy. Although both modalities yield highly standardized images, hardware up until now was incapable of handling such data. The proposed approach combines image processing techniques and advanced deep learning techniques. The proposed approach achieves automated classification of skin lesions using images.

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This is a challenging task because of the close-grained variability in skin lesions. The main contribution of this paper is stated as follows:

- This research uses an advanced deep learning architecture to classify the skin cancer from the given images.
- The capsule architecture used in this paper is modified in such that it overcomes the drawback of pooling layer. CapsNet has a drastic advantage in its capable to distinguish the spatial relationship between the features by making them translation-equivariant and viewpoint-equivariant. Hence, the CapsNet is capable of detecting the cancer spot anywhere in the image.
- Experimental validation is carried out using BioGPS and HAM 10000 – Skin cancer dataset.

Background

Deep learning in medical image classification is nothing new. Researchers around the world are utilizing Convolutional Neural Networks to solve common problems in the field of image classification. CNNs were built at first to classify images; they do so by using successive layers of convolutions and pooling. When training a traditional CNN, we only care about whether the model predicts the right classification or not. The pooling layer in a convolutional block is used to reduce the data dimension and achieve spatial invariance, which means regardless of where the object is placed in the image, it identifies the object and classifies it. While this is a powerful concept, it has some drawbacks.

The drawback of a CNN is that during pooling it tends to lose a lot of useful information while performing tasks such as image segmentation and object detection. The pooling layer loses the required spatial information due to the rotation, location, scale, and different positional attributes of the object. Hence, the process of object detection and segmentation becomes difficult and the outputs are sensitive to small changes in the inputs. This is a problem when detailed information must be preserved throughout the network. CNNs accumulate sets of features at each subsequent layer, starting with finding edges, shapes, and finally objects. However, little information about the spatial relationship between these features such as size and orientation, is retained. Therefore, the result is ambiguous conclusions due to samples of the same images with different orientations being considered as different images. One way to overcome the problem is with excessive training for all possible angles, which ultimately takes a lot more time and computational efficiency. This issue is addressed by building complex architectures around CNNs to recover some of the lost information. While modern CNN architecture has managed to reconstruct the positional information using a combination of advanced techniques, it still requires more enhancements to achieve 100% efficiency. Another notable shortcoming of the pooling layer is if the position of the object is slightly changed, the activation does not seem to change with its proportion. This leads to good accuracy in terms of image classification, but results in poor performance.

Capsnet in Classification

A CapsNet is a collection of capsules. A capsule is a group of neurons representing an entity present in an image. A capsule provides two values corresponding to an entity it represents. The first is the probability that the entity represented by a capsule exists in the image. The second is the initial parameters for that entity.

The probability value of the capsule conveys the existence of the object in the image. These initial parameters represent certain characteristics of the entity represented by the capsule, which includes position, size, hue, position, saturation, etc. Additionally, the initial parameters of the capsule include its geometric properties and color statistics (color, length, breadth, and texture). As mentioned, a capsule is a collection of neurons. Each neuron can be considered a property of the entity and in this case the capsule encompasses 4 neurons for each property. This can be represented as a vector with parameters as x1, x2, x3, and x4. The probability of existence is the length of this vector. The probability of the presence of the entity can be derived from these parameters as:

$$P = \sum_{i=1}^{n} \sqrt{x_i^2} \quad \ldots (1)$$

But this probability value must lie within the range [0,1]. The capsule output must be transformed to fit into this range. This non-linear transformation of the output is called the squashing function. This function serves as an activation function for the Capsule Networks. The Capsule Network, like other neural networks, is structured with different layers. There are two basic layers in the Capsule Network known as Primary layer and Secondary layer. The capsules in

the primary layer or the lowest layer are termed as primary capsules. The capsules in the secondary layer or higher layers are called the routing capsules. The primary capsules represent small regions of an image, biologically known as a receptive field. These capsules try to locate the existence of an entity or an object with a probability based on different geometric parameters. The routing capsules in the higher layers recognize more complex objects which are composed of smaller entities. Routing by agreement is one of the important algorithms of CapsNet by which the lower layers and the higher layers work together to recognize the presence of an object in the image. This routing between the capsule leads to a coupling effect.

When the capsules in the lower layer acknowledge the higher layer about the presence of a high-level entity, the capsules in the higher layer will send feedback to the lower layer capsules. The feedback helps improve the output manipulated by the lower layer capsules. The primary capsule layer in a CapsNet is usually a combination of regular convolutional layers which helps in extracting the primary features of the images through feature maps. The feature maps are reshaped accordingly and with the assistance of the squashing function, the output of the primary capsule layer will be a vector of length between 0 and 1.

Related works

Machine learning algorithms have been widely applied to the problem of skin cancer classification. Though insufficient for advanced classification, logistic regression methods are used to complete basic classification and test the efficacy of feature engineering.[3] Support vector machines (SVM), Bayesian classifiers, and decision tree classifiers have all been explored.[4,5,6] Artificial neural networks have been applied using many methods including multi-layer perceptron and back propagation.[5]

Convolution neural networks[7,8] exemplify their flexibility and predictive power when applied to skin cancer classification. In recent years, many applications aiming for maximum diagnostic classification have utilized CNNs. CNNs[9] require a large dataset in order to properly generalize its prediction. In order to overcome this, many are trained using transfer learning. Transfer learning uses pretrained features to expedite the recognition of legion properties like asymmetry and border hardness. For application to skin cancer diagnosis, deep learning image classification networks like Inception, ResNet, AlexNet, VGG are some predominant networks used in transfer learning.[10–14] One of the most widely used, pretrained models is InceptionV3 presented by Wojna *et al.*[15] The CNN was trained using the ImageNet Large Visual Recognition Challenge dataset, where it placed second.[16–19] AlexNet was the first-place contestant in the same competition in 2012 and has since seen transfer learning applied to many image analysis domains.[20]

It is difficult to compare deep learning architectures addressing the problem of skin cancer classification, because studies often use unavailable or partially unavailable datasets for training and testing.[21] The classes within the dataset are rarely proportional and often are starkly disproportional. Beyond this, model formulation varies greatly, and evaluation techniques may not align.

Ensemble learning[22] is a supervised learning algorithm that makes a single prediction based on the hypotheses of two or more existing predictive models. These models may differ in architecture or differ in training set.[14,22,23] Ensembles combine the hypotheses of each model and produce a final prediction that potentially could differ from all its component models. This shows that an ensemble architecture can create a more complex hypothesis function than can be achieved through a singular model. Ensemble methods often place among the top in online machine learning competitions.

Estava *et al.*[24] presented a deep learning model trained on 129,450 images. This method uses a GoogLeNet Inception v3 pretrained with the ImageNet database. This landmark study can claim diagnostic rates on par or better than dermatologist evaluation.

An ensemble classifier proposed by Bi *et al.* [12] used the technique of training the same model on slightly varying datasets. One ResNet was trained to classify between melanomas, seborrheic keratosis, and nevi. One ResNet was a binary classifier trained to classify melanoma versus any other class. The last ResNet was a similar one-vs-all binary classifier aiming to diagnose seborrheic keratosis. Pretraining using the ImageNet dataset was applied to each model. With only 150 dermoscopic images the method achieved an overall ROC AUC of 0.915 over all classes.

Milton[14] experimented with modern deep learning models using the ISIC 2018 Melanoma Detection

Challenge dataset. The study used the PNASNet-5-Large, Inception ResNetV2, SENet154, InceptionV4, along with an ensemble classifier. Each classifier was pretrained on the ImageNet using a tactic of first training on a largely frozen network, and then allowing the final few layers to be precisely tuned by the limited dataset. Results show PNASNet-5-Large had the highest validation score of 0.76, and the ensemble performed comparably with a validation score of 0.73.

Afshar *et al.*[25] presented a comparison of CapsNet architectures for classification of MRI images containing brain tumors into three classes. The best performing architecture had one convolution layer and 64 feature maps, and it achieved an accuracy of 86.56%. A standard CNN trained on the same 3,064 MRI images only produced an accuracy of 72.13%. This is due to the CapsNet architecture's ability to train with a small number of images. The CapsNet rather had the issue of over fitting and required an early-stopping approach. Both networks performed better using segmented tumor data as input rather than whole brain images.

Iesmantas, Alzbutas *et al.*[21] proposed a convolutional Capsule Network, for classification of four types of images of breast tissue biopsy using 400 hematoxylin and eosin stained breast histology microscopy images. No transfer leaning was used, and the Adam optimizer was utilized with a learning parameter of 0.0001. 75 percent of the images are used for training and the other 25 percent underwent 5-fold cross-validation. Cross-validation resulted in an average accuracy of 87 across the four classes.

Zhang *et al.*[13] proposed a modern CNN classifier that leverages an algorithm that was designed using observations from the hunting pattern of whales. A concern with many optimization techniques it that the model will train to a local optimum rather than a global one. Mirjalili *zhan.*[16] designed the Whale Optimization Algorithm (WOA) in order to better determine the global optimum for model tuning. The proposed model was tested on two benchmark datasets (Dermquest, DermIS) and comparatively evaluated among 10 other diagnosis techniques. The proposed classifier outperformed all other classifiers in both sensitivity and specificity.

CNNs have become the field leader in skin legion classification due to their high precision.[13–15] Yet they often cannot be properly trained and tested due to the lack of a unified skin legion dataset.[21] As such, many studies leverage systems that can be trained with fewer images, such as ensemble models.[22] Comparison of models is difficult and no one model has shown to effectively classify all skin legions.[24–26] Beyond this, traditional CNNs have the information loss in the pooling layer.[27–30] This means that they grant translational invariance but not rotational invariance.[31] To achieve this CapsNet models use vector-output capsules and max-pooling with routing by agreement, unlike scale-output feature detectors of CNNs.

Proposed method

The proposed convolution layer uses a traditional convolution network with the ReLUactivation function to extract the basic features of the image. The input image provided to the input layer is resized to 28×28 after applying initial preprocessing step. Each pixel is considered as x_i. The input layer is of size 28*28*1.

The subsequent layers of the CapsNet are the convolutional layer and the capsule layer which are mainly needed for the detection of the entities needed for classification. The CapsNet architecture, as shown in Fig. 1, is similar to a general neural network architecture except for the introduction of the capsule layer block consisting of a sequence of capsule layers. This layer is used to divide features into capsules. This part contains a convolution layer with a kernel size of 9 and a stride size of 1 with filter 256. This layer performs the dot product between the filter and the blocks of input images. The next capsule layer is of size 32. The output size is 20×20×256 (20×20×32×8), and the dimensionality of each capsule is 8.

The final layer in the proposed method is a fully connected layer, usually using the SoftMax activation

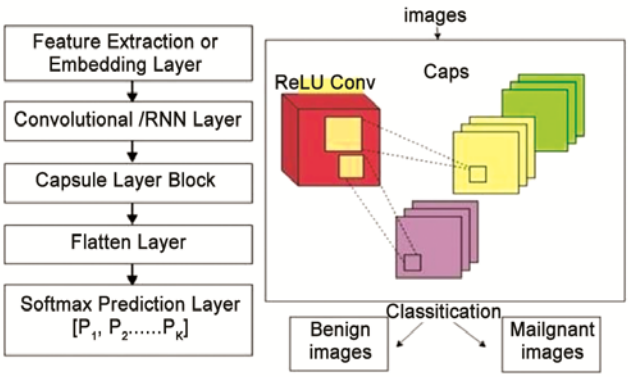

Fig. 1 — A Basic CapsNet Architecture

function for classification. Here, the probabilities returned by the SoftMax activation function for each input are assigned to one of the mutually exclusive classes. Automatic classification of skin cancer based on the object skin lesion images helps to improve dermoscopic analysis and examination since there can be a fine-grained difference in the appearance of skin lesions. The SoftMax activation function is given in Eq. 2.

$$softmax = (x_i) = e^{x_i} / \sum_{i=1}^{n} e^{x_i} \quad \ldots (2)$$

The loss of the proposed model is predicted with the cross entropy as in Eq. 3.

$$Loss(p,q) = -\sum p(x_i)\log(q(x_i)) \quad \ldots (3)$$

where p is the probability distribution of each pixel. The proposed method is graphically represented in Fig. 2.

Results and Discussion

The proposed approach is validated using BioGPS and HAM 10000 – Skin cancer dataset. The sample dataset is shown in Fig. 3. Transfer learning is used to train the Capsule Network used in this research to identify the skin cancer cell from the dermatological photo. Transfer learning is an efficient method used for training the CNN. The datasets used for experimental validation are small and training from them is not effective. To address this, the first few layers of the network are used to train a linear classifier on the output from these initial layers. The method works by reusing the already learned features of a benchmarked neural network. Here we used DNN which has more than 1000 categories with a thousand images in each category. The experimentation is carried out in a Windows 10 machine with NVIDIA Titan Xp GPU and Intel Xeon - Octo- core processor, 128 GB RAM. The accuracy rate for both training and testing are shown in Fig. 4. The loss rate for both training and testing are shown in Fig. 5. Datasets of BioGPS and HAM 10000 contains 7 different classes of images namely:akiec, bcc, bkl, df, mel, nv, vasc.

The network is tuned by considering the number of epochs, rate of learning and the size of batches. Though empirical experimentation the number of epochs is determined to be 50. The learning rate was estimated to be between 0.01 and 0.001 and found to produce better performance on CapsNet using 0.001. The batch size considered is 10. The experimentation

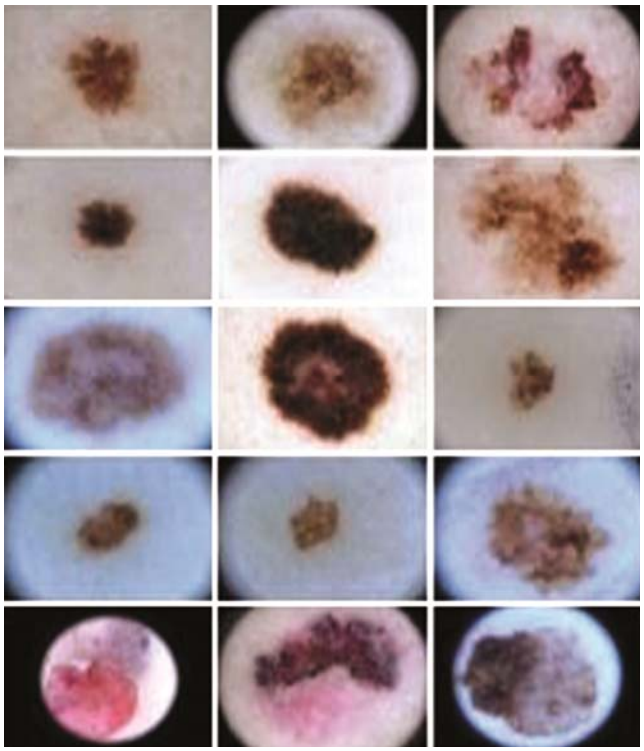

Fig. 3 — BioGPS and HAM 10000 - Skin Cancer Dataset

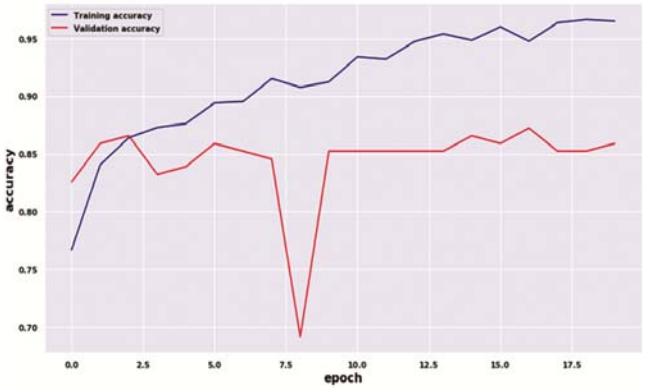

Fig. 4 — Accuracy vs. Epoch

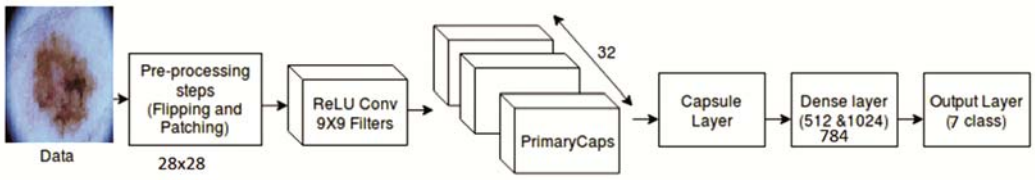

Fig. 2 — Architecture of Proposed Method Sample

is performed by considering 7010 training images and 3005 testing images.

The configuration details of the capsule network are given in Table 1. The first convolution layer is applied with 256 filters with kernel size 9 resulting in an output of 20×20×256 (this is obtained by 28−9+1). The parameters generated at this layer are 20992. These learning parameters are obtained by 9×9×1×256 which is same in every layer.

The accuracy of the proposed network in regard to epochs is shown in Fig. 4. The loss vs. epochs comparison, it is depicted in Fig. 5 that the loss is decreased at every epoch.

The performance of the proposed network is evaluated using the measures precision, recall, f1-score and the support. From Table 2, the network showed approximately 92% of precision, 91% of recall and f1-score and a support of 938 which is outperforming all the existing techniques for classification of skin cancers. It is clearly seen from Fig. 6 that the CapsNet is capable to detect malignant accurately. The performance analysis of the CapsNet model and the state-of-the-art models are shown in Fig 7. From Fig. 7a it is clear that the proposed model achieves nearly an accuracy of 92% which is greater than the state-of-the-art model.[24,25,20] From Fig. 7b it is clear that the false positive rate for the CapsNet model is much lesser than the state-of-the-art models.[24,25,20]

The confusion matrix of the proposed network is depicted in the Table 3.

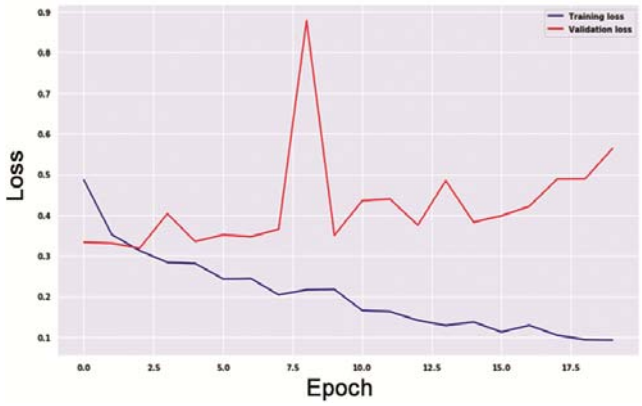

Fig. 5 — Loss vs. Epoch

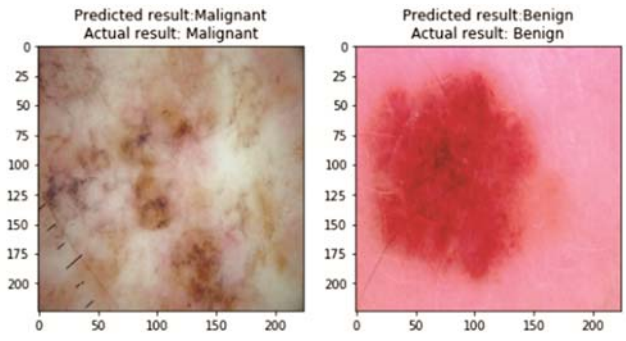

Fig. 6 — Results: Skin cancer classification

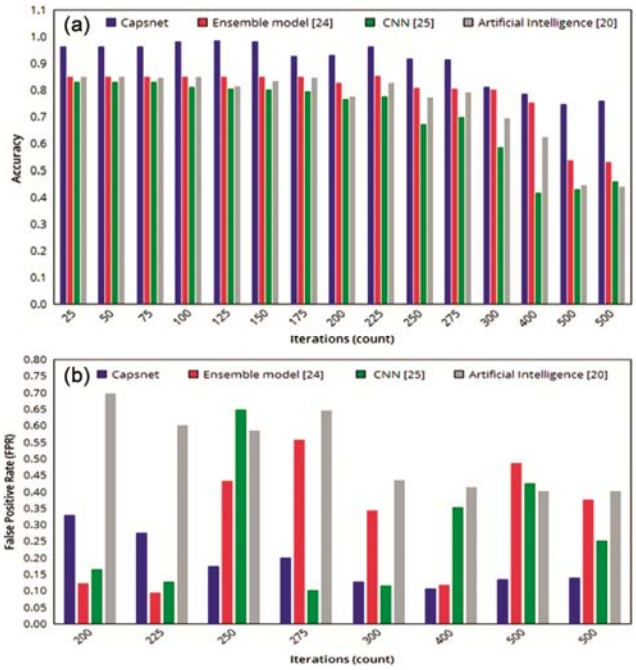

Fig. 7 — Performance analysis – CapsNet vs state of the art model

Table 1 — Network configuration for skin cancer classification

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 28, 28, 1)	0	
conv1 (Conv2D)	(None, 20, 20, 256)	20992	input_3[0][0]
conv2d_2 (Conv2D)	(None, 6, 6, 256)	5308672	conv1[0][0]
reshape_2 (Reshape)	(None, 1152, 8)	0	conv2d_2[0][0]
lambda_2 (Lambda)	(None, 1152, 8)	0	reshape_2[0][0]
digitcaps (CapsuleLayer)	(None, 7, 16)	1040256	lambda_2[0][0]
input_4 (InputLayer)	(None, 7)	0	digitcaps[0][0]
mask_2 (Mask)	(None, 16)	0	input_4[0][0]
dense_4 (Dense)	(None, 512)	8704	mask_2[0][0]
dense_5 (Dense)	(None, 1024)	525312	dense_4[0][0]
dense_6 (Dense)	(None, 784)	803600	dense_5[0][0]
out_caps (Length)	(None, 7)	0	digitcaps[0][0]
out_recon (Reshape)	(None, 28, 28, 1)	0	dense_6[0][0]

Table 2 — Performance measures of Capsule Network

classes	precision	recall	f1-score	support
akiec	0.50	0.42	0.46	26
bcc	0.41	0.87	0.55	30
bkl	0.77	0.13	0.23	75
df	0.10	0.50	0.17	6
mel	0.28	0.49	0.35	39
nv	0.94	0.91	0.92	751
vasc	0.67	0.73	0.70	11
avg / total	0.94	0.91	0.91	938

Table 3 — Confusion matrix for classes of skin

	akiec	bcc	bkl	df	mel	nv	vasc
akiec	11	3	2	3	5	2	0
bcc	1	26	0	1	2	0	0
bkl	6	5	10	2	24	28	0
Df	0	0	0	3	0	3	0
mel	3	3	0	2	19	11	1
Nv	1	27	1	19	19	681	3
vasc	0	0	0	0	0	3	8

The proposed method has shown good classification of skin cancer images when compared to existing methods in the literature. The CapsNet architecture overcomes one of the important drawbacks of the Convolutional Neural Network. A CNN's architecture is composed of a sequence of convolutional, pooling, and fully connected layers. The Max Pooling layer is a type of routing mechanism. Only the active feature from that layer is passed to the further layers, but the higher layers do not provide any feedback to the routing from the pooling layer. This is introduced in the CapsNet with a dynamic routing mechanism. Additionally, the CapsNet has the capability to recognize tumors with few iterations, whereas the existing networks like CNN, need training on huge image sets. This indicates the significance of the CapsNet in the image recognition field. CapsNet can be utilized to achieve a performance comparable to the dermatologists.

Conclusions

In this paper, an approach to detect skin cancer that is robust enough to segment the cancer region was proposed. The training images are equally weighted so that the distribution among the samples are best approximated and further used for classification in the CapsNet model. From the experimental results, it is concluded that the proposed approach is better in terms of segmentation and classification than the state-of-the-art classifiers available for skin cancer detection. In the experiments, various features were compared, and it was determined that the proposed approach is more sensitive than the state-of-the-art classifiers.

The proposed model was trained using Ham10000 dataset which consists of 10015 dermatoscopic images. For future work, we have a plan to use different data augmentation techniques to increase the data set size. In addition to that to improve the classification efficacy further, we will work towards adding more clinical data covering all diverse aspects like skin type, race, age, etc. Further research will also focus on adding features to incorporate the patient's medical record in addition to dermatoscopic images to facilitate enterprise-level computer-aided diagnosis tool development.

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