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Abnormality Detection in Musculoskeletal Radiographs Using Capsule Network

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ABSTRACT To treat the diseases or injuries of the joints, bones, muscles, and spine in both adult and pediatric imaging the musculoskeletal radiographs bring a significant depth of expertise. Abnormality detection in the musculoskeletal study is backbreaking as more than 1.7 billion people are affected by musculoskeletal condition (BMU, 2017). Hence if we want to create enough opportunity to treat a maximum amount of patients, machine learning and deep learning can play a crucial role. CNN is an excellent deep learning method for image classification and other computer vision tasks. But CNN has exhibited some serious limitations when the images are rotated and deformed. Hence capsule network architecture is introduced in this paper for musculoskeletal radiographs abnormality detection and this capsnet architecture has shown very promising features that can help to vanquish the limitations of CNN. In addition, this capsule network has scored 10% higher kappa score than 169 layer densenet using less training data in the case of musculoskeletal radiographs abnormality detection. This feature of capsule network can help to use deep learning in such cases where an aggregate of a large amount of data is not possible. For image quality investigation, blind image spatial quality evaluator (BRISQUE) and naturalness image quality evaluator (NIQE) scores are measured and it is found that when the pixel size of the resized images are more close to the pixel size of the original images, we get a better approximation. Hence in the case of musculoskeletal radiographs abnormality detection, our method outperforms state-of-the-art method using a less amount of training data.

INDEX TERMS Capsule network, routing-by-agreement, squashing, margin loss, Cohen's kappa statistic.

I. INTRODUCTION

Circumstances, ranging from work accidents and sports injuries to genetics and lifestyle choices can be the cause of Musculoskeletal problem. Injuries, osteoarthritis of the knee, osteoporosis of the bones and many other joint or muscle issues are the result of Musculoskeletal problem. Proper diagnosis and abnormality detection are very important for further treatment. But a large number of patients has made this task very difficult and time-consuming and so, computer-based automatic detection of abnormality can become very handy as well as time-saving.

Various machine learning processes have played a significant role in medical image classification. Decision Forests [1] has shown significant results in image classification. Support vector machine [2], [3] is another approach for medical image classification. K-Means clustering [4], Integrating spatial fuzzy clustering [6], Gaussian model [7] are also very popular algorithm used for medical image classification. In contrast in the field of deep learning, Convolutional Neural Network (CNN or ConvNet) [8], [9] has been used extensively in classifying images and segmentation problems. But CNN is not any state of the art architecture. It has shown some major drawbacks. If CNN is trained with data sets of images having an orientation to identify whether it contains a specific type and if it is not trained with images having orientation similar to that type, then for images rotated and deformed, CNN classifier does not produce a correct classification. These limitations of CNN come from the fact that its neurons are activated based on the chances of detecting specific feature. Properties of a feature such as orientation, size, velocity, color etc are not considered by neurons. Determining the spatial relationship in CNN requires precise location of features in the input image. To achieve translation invariance

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MaxPooling is performed. Translation Invariance indicates that CNN will classify the input image in the same way regardless of how the information within the image is shifted and the features location information is lost at the Pooling layer. Again the performance of the neural network depends on the depth of the architecture. Adding more layers will reserve more information and improve performance. But that also increases the computational complexity and computational cost.

In contrast information at the neuron level is stored as vectors in capsule network rather than scalars like neural networks. The vector output of a capsule uses a powerful mechanism, dynamic routing [10]. These vectors contain information about: spatial orientation, magnitude/prevalence, and other attributes of the extracted feature. The main objective of this paper is to:

- Find an improved architecture for estimating abnormality in the musculoskeletal condition which can maximize the abnormality detection rate
- Examine the ability of capsule network in the case of image classification and processing and also investigate the over-fitting problem in capsnet.
- And also want to find out whether capsnet can outperform the convolutional neural network

MURA [12] dataset is used for training and testing the capsule network. In MURA dataset a 169 layer neural network(densenet) provides better performance in comparison to the best radiologist performance in detecting abnormalities on finger and wrist studies. This model performs lower than best radiologist performance in case of detecting the abnormality in elbow, forearm, hand, humerus and shoulder studies. Hence the aim of this paper is to find a more suitable architecture that can identify the abnormality in all of the cases more accurately than the previous method.

II. BACKGROUND AND RELATED WORKS

A. PREVIOUS WORKS

Medical image classification is an attractive topic in the field of computer vision and biomedical image processing. Machine learning algorithms and deep learning have been used for medical image processing and they deliver impressive result in such cases. These machine learning methods have achieved reasonable accuracy in many domains but they generally require very specific hand engineered features to work which greatly diminishes their ability to generalize to related problems. In contrast, neural network extracts feature by its own.

Capsule network also extracts features by its own but conserves spatial information through vector output. In ''BRAIN TUMOR TYPE CLASSIFICATION VIA CAPSULE NETWORKS'' [13] capsule network is used to classify brain tumor. It is found that capsnet performs better than CNN with less training data. In ''Capsules for Object Segmentation'' [14] a convolutional-deconvolutional capsule network called SegCaps based on capsule network is proposed which shows strong results for the task of object segmentation.

B. PROBLEM DEFINITION

Finding abnormality in musculoskeletal radiographs is a very difficult task and if automatic detection of abnormality can be introduced, it would be very helpful for further diagnosis and treatment. In this regards, MURA dataset was published with 40,561 images from 14,863 studies. In this paper, a capsule network is designed to classify normal and abnormal condition and compared the result with densenet architecture.

III. CONVOLUTIONAL NEURAL NETWORKS AND ITS LIMITATIONS

The convolutional neural network works on three steps: convolution, relu, pooling. These steps create each layer and adding more layers create a deep convolutional neural network. Each layer receives input from the previous layer. Convolution the main building blocks of a CNN is a mathematical combination of two functions to produce a third function and merges two sets of information. This convolution is computed between input data and filter. They produce third information known as feature map. For adding non-linearity relu is used. Then comes the pooling layer which is used to decrease the parameter and for convolutional neural network maxpooling is extensively used. In the end, they all connected to a fully connected layer.

Comparing CNN with human brain some serious shortcomings have been found. CNN suffers from poor translational invariance and lack of information about orientation. CNN faces a problem when objects are rotated or when lighting conditions are changed. Again, pooling is an important part of CNN structure. Pooling which is introduced to reduce redundancy of representation and reduce the number of parameters, recognizing that precise location is not important for object classification. Maxpooling helps to speed up the CNN. Maxpooling just picks the neuron with the highest activation but it causes some serious labyrinth by losing the feature location information. For this reason, CNN cannot identify any kind of deformation or rotation in the image and so they need enormous training data and rotation of data.

All these aforementioned drawbacks are the inspiration behind the capsule network which is more robust to translation and rotation. In capsule network scaler output is replaced by vector and max-pooling is replaced by more effective routing-by-agreement which prevents data information lose.

IV. PROPOSED METHOD FOR MUSCULOSKELETAL RADIOGRAPHS ABNORMALITY DETECTION

In this paper, the capability of capsnet in classifying musculoskeletal radiographs is studied by designing a capsnet for detecting the abnormality in musculoskeletal radiographs. Data is preprocessed and then the processed data is fed in the designed network.

A. PREPROCESSING DATA

As a part of preprocessing, image data is resized and normalized. As the radiographs are of different size, resizing is needed to get an equal image size. At first they are resized

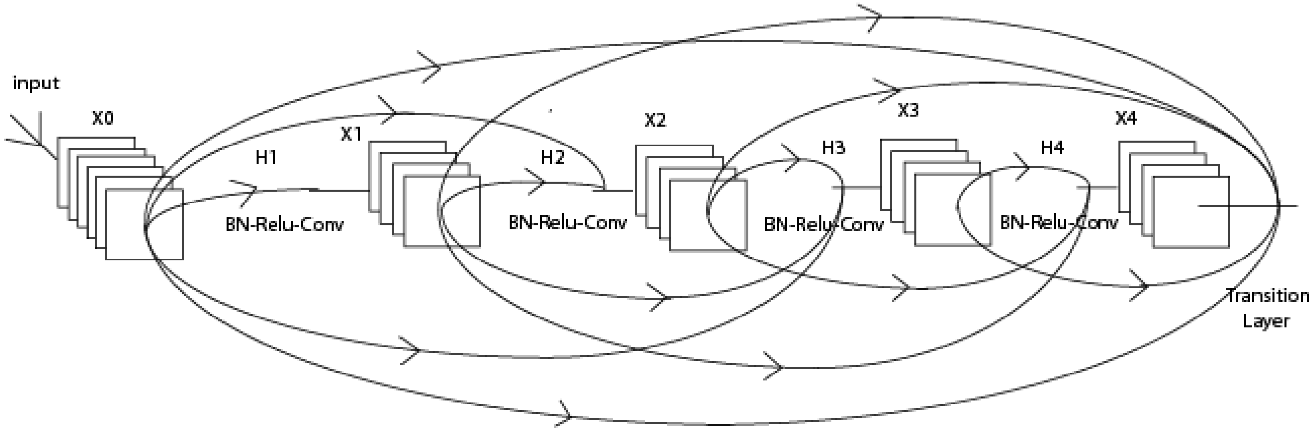


FIGURE 1. A 5-layer densely connected convolutional neural network(densenet).

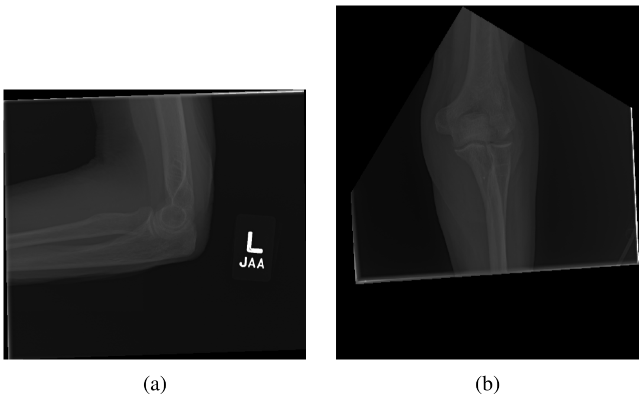


FIGURE 2. Original images from the dataset showing variability in image size. (a) Abnormal elbow. (b) Normal elbow.

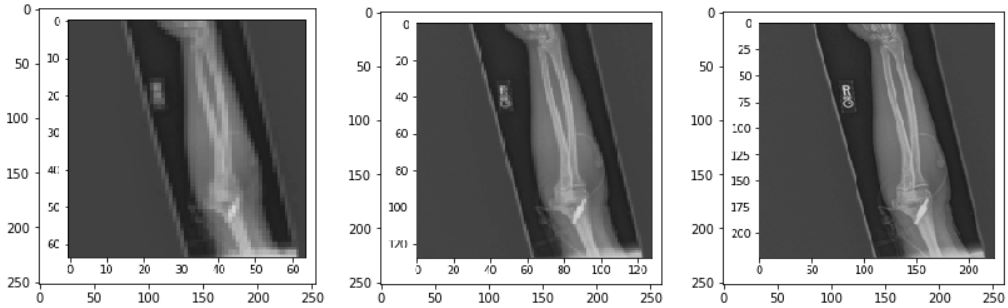
to 64 × 64 pixel size. Then they are resized to 128 × 128 pixel size and at last all the images are resized to 224 × 224 pixel size. All these three different types of resized images have some merits and demerits when they are used to train the network. When the image size is 64 × 64, most of the features are lost and as a result very poor image quality is obtained which provides very low accuracy and very high loss. But when the feature maps are reduced, it takes very small amount of time to train the network. In the second case, when the image size is 128 × 128 accuracy is improved and loss is reduced. But as the feature maps are increased it takes almost three times more time to train the network. And for the last case when the image size is 224 × 224 the best accuracy is obtained and loss is also very small. But it takes more time than the first two types mentioned above to train. From fig.3 the discussion mentioned above can be related. Table 1 shows the Blind Image Spatial Quality Evaluator (BRISQUE) and Naturalness Image Quality Evaluator (NIQE) score [15], [16]. The BRISQUE and the NIQE algorithms calculate the quality score of an image with computational efficiency after the model is trained and in this case MURA dataset is used for training purpose. Lower BRISQUE and NIQE score indicate that the resized images conserve more features or we lose less features after resizing. Images are also normalized as a part of preprocessing. Hence fig.3 is a presentation of resized and normalized images. To get a better result in CNN, data augmentation is needed in the training phase but capsule network can perform better without data augmentation in the training phase and for that reason, we do not apply data augmentation while training capsule network but we have used data augmentation while training densenet. In the result section, we have compared the accuracy between capsule network and densenet and the effect of resizing and normalizing of images with their respective accuracy is also described.

B. GENERAL STRUCTURE OF CAPSULE NETWORK

Many small groups of neurons called capsules create each layer in a capsule network. At any capsule layer n, a set of capsule types consists of $a^n \times b^n$ grid of z^n dimensional child capsule and this is the output of layer n-1. At the next $(n+1)^{th}$ layer of the network, a set of capsule types is an $a^{n+1} \times b^{n+1}$ grid of z^{n+1} dimensional parent capsules, where $a^{n+1} \times b^{n+1}$ is the spatial dimension of the output of layer n. Output vector of a capsule represent the probability that the entity represented by the capsule is present in the current input. Then non-linear ''squashing'' function is used to ensure that short vectors get shrunk to almost zero length so that it does not route in the mother capsule and long vectors get shrunk to a length below 1. If v_j is the vector output of capsule j and s_j is its total output then they used the following non-linear function

$$v_j = \frac{\| s_j \|^2}{1 + \| s_j \|^2} \frac{s_j}{\| s_j \|} \tag{1}$$

The input to a mother capsule s_j is a weighted sum of prediction vectors $\hat{\boldsymbol{u}}_{ji}$ is calculated from the output of child capsules by multiplying the output u_i of a child capsule output by a



(a) (b) (c)

FIGURE 3. Down sampling degrade image quality and as the pixel size is increased more features are included. (a) image size 64 × 64. (b) image size 128 × 128. (c) image size 224 × 224.

weighted matrix $\boldsymbol{W}_{ij}$

$$s_j = \sum_i c_{ij}\hat{\boldsymbol{u}}_{ji} \tag{2}$$

$$\hat{\boldsymbol{u}}_{ji} = \boldsymbol{W}_{ij}\boldsymbol{u}_i \tag{3}$$

Coupling coefficients c_{ij} indicates the coupling or bonding between the mother or higher capsule and the child or lower capsule and is calculated by using softmax function

$$c_{ij} = \frac{\exp b_{ij}}{\sum_k \exp b_{ik}} \tag{4}$$

where b_{ij} is the log probability that indicates whether capsule i should be coupled with capsule j and it's initial value is set to 0 at the beginning of the routing by agreement process. The log probabilities is updated in the routing process based on the agreement between $\boldsymbol{v}_j$ and $\hat{\boldsymbol{u}}_{ji}$ and so they produce a large inner product as

$$a_{ij} = \boldsymbol{v}_j.\hat{\boldsymbol{u}}_i \tag{5}$$

This agreement is treated as if it is a log likelihood and is added to the initial logit, b_{ij} before computing the new values for all the coupling coefficients linking capsule i to higher level capsules.

C. MARGIN LOSS

Margin loss is introduced to ensure intraclass compactness and interclass separability. In capsnet margin loss is used to describe the presence of any class in corresponding capsule. Proper identification of classes reduce the margin loss. As the capsules outputs are vector so the margin loss depend on the length of the vector. If any entity is present in any capsule output then its instantiation vector must have the largest length means the top-level capsule for digit class k to have a long instantiation vector if and only if that entity is present in the image. So a separate margin loss, L_k is introduced for each digit capsule k:

$$L_k = T_k max(0, m^+ - \|v_k\|)^2 + \lambda(1-T_k) max(0, \|v_k\| - m^-)^2 \tag{6}$$

where T_k is 1 whenever class k is actually present, and is 0 otherwise. Terms m^+, m^-, and λ are hyper parameters to be indicated before the learning process.

D. PROPOSED CAPSNET ARCHITECTURE FOR MUSCULOSKELETAL RADIOGRAPHS ABNORMALITY DETECTION

The structure is designed for three types of image size, they are 64 × 64, 128 × 128 or 224 × 224. Here image size of 224 × 224 is only considered for describing the structure. The summary of the layers of the proposed model which is illustrated in Fig.5 is as follows:

- The dataset contain images of variable sizes hence they are resized to 224 × 224 image size. This is the input in the input layer.
- After the input layer the first convolutional layer, conv1 which has 256, 9 × 9 convolutional kernels with stride of 1 and RELU activition function is activated. The output of this layer is the input to the primary capsules. Pixel intensities are converted to the activities of local feature detectors in this layer.
- Second layer is a convolutional capsule layer having 32 channels of convolutional 8D capsules. Primary capsule 32 × 104 × 104 capsule output and each output is an 8D vector. Each capsule is connected like a 104 × 104 grid and each is sharing weights with each other.
- The final capsule layer is a "class capsule" includes 2 capsule and each capsule has a dimension of 16.
- Additional reconstruction loss is used to encourage the class capsules to encode the instantiation parameters of the input. The output of the class capsule is fed into a decoder consisting of 3 fully connected layers that model the pixel intensities. This decoder will learn to reconstruct the input images based on the output of the capsule network. This will force the capsule network to preserve all the information required to reconstruct the digits, across the whole network. This constraint regularizes the model: it reduces the risk of overfitting the training set, and it helps generalize to new types. The decoder part is composed of three fully connected

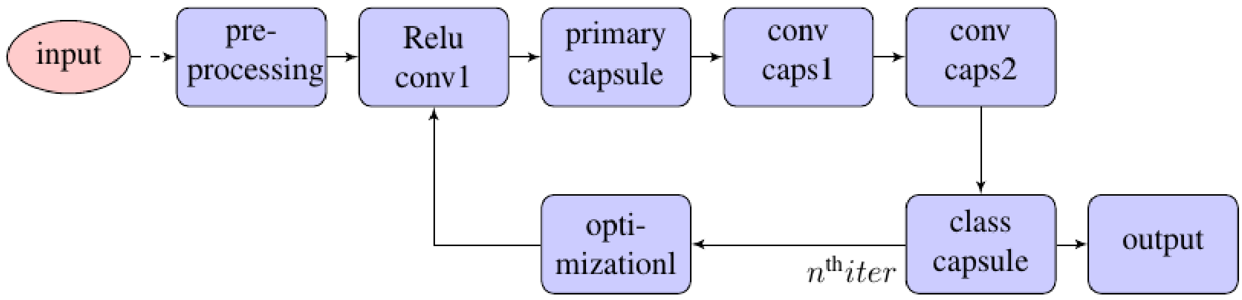


FIGURE 4. A flowchart indicating the whole process of Musculoskeletal abnormality detection using capsule network.

layers having 512, 1024 and 50176 neurons respectively. The sum of squared differences between the outputs of the logistic units and the pixel intensities is minimized. We scale down reconstruction loss by 0.0005 so that it does not dominate the margin loss during training.

- As mentioned in the aforementioned discussion, a squashing function is needed to squash the output but a problem may arise as in some cases || s_j || can be zero and then we will get a undefined v_j. Hence a very small value ϵ is added with it so that v_j does not become undefined. In fig.4 a flowchart is introduced for better understanding of the process.

V. EXPERIMENTAL SETUP

A. DATASET

MURA dataset is used to feed the network and the result is compared with the result obtained by using 169 layer densenet. The dataset contains seven types of upper extrem musculoskeletal radiographs and classified into normal and abnormal class. In total, MURA dataset contains 14656 images. Total 13457 training images and 1199 validation images. Among them 8941 images are normal and 5715 images are abnormal. Cohen's kappa statistic is used to compare the results.

B. TRAINING AND TESTING CONDITION

Different types of resized images are used to train the network. Only 50% of data is used for training and validation and rest of the data is used for testing purpose. Randomly selecting the training and validation data and performing the training and testing task for several times the average of the results is taken. Routing is an important feature of capsnet. Different number of routing is used to see the effect. 10 iterations are used. m^+ is set equal to. 9 and m^- is set equal to. 1. λ is set to. 5. The whole training data set has not been used to train the network. As a result training time has reduced significantly.

VI. RESULTS

The final quantitative results of these experiments are discussed in this section.

TABLE 1. Accuracy obtained using variable image size and BRISQUE and NIQE score.

Image size	Average BRISQUE score	Average NIQE score
64 × 64	26.06	9.55
128 × 128	22.82	6.24
224 × 224	17.034	6

A. OBJECTIVE EVALUATION OF IMAGE SIZE

In table 1 BRISQUE and NIQE score for different image sizes have been compared. BRISQUE score and NIQE score both indicate the image quality by comparing them with reference images. In our used dataset, the reference images are the original images having a variable pixel size and from the table 1, it is clear that as we decrease the image size, the BRISQUE and NIQE score increase. And when we increase the image size, BRISQUE and NIQE score decrease. Lower BRISQUE and NIQE score indicate that the transformed images are more close to the original images.

As mentioned earlier, decreasing the image size lose information means when decreased the image size or downsample the image, image loses important features. Table 1 also justifies the reason for taking 224 × 224 pixel size of the images as this image size has the lowest BRISQUE and NIQE score.

B. COMPARISON OF RESULTS OBTAINED BY VARYING ROUTING NUMBER

Routing by agreement is an iterative process where routing algorithm acts like an orientation-popularity filter. Input from lower level capsule will send to the higher level capsule that agrees with its input.

From table 2 to 5 it can be observed that the number of routing effects the accuracy. As the number of routing is increased, accuracy gets better. But a problem arises with the increasing number of routing and this increased number of routing makes the network overfit for hand and humerus data. From fig.6 it can be seen that hand and humerus data suffer from overfitting problem. Theoretically, routing helps the child capsule's output to find the best route that agrees with its input, more and more routing can overfit

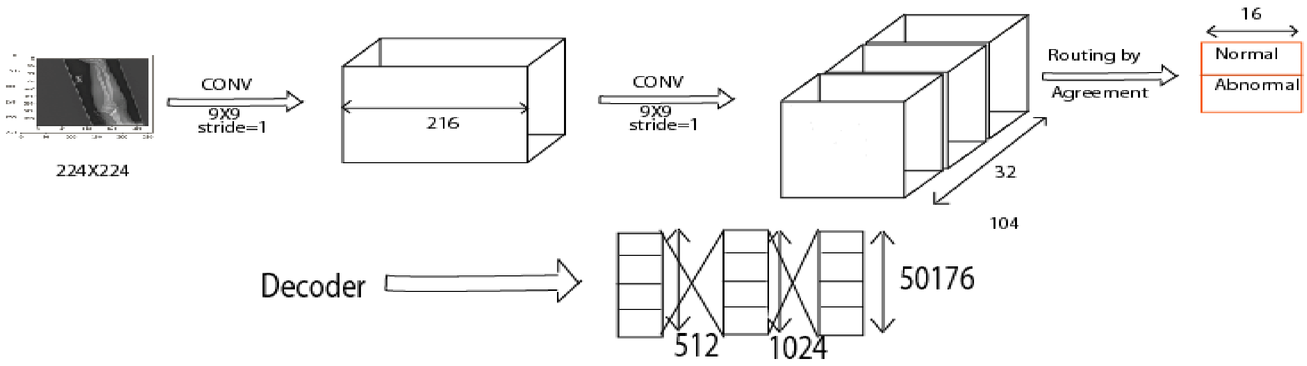


FIGURE 5. Proposed Capsule Network architecture.

TABLE 2. Accuracy obtain using one routing.

Image	Training accuracy	Validation accuracy
Finger	35.3%	29.7%
Humerus	36.27%	31.43%
Elbow	32.8%	30.1%
Forearm	38%	40.5%
Hand	39.75%	35.8%
Shoulder	42.73%	34.4%
Wrist	37.77%	33.83%

TABLE 3. Accuracy obtain using two routing.

Image	Training accuracy	Validation accuracy
Finger	65.9%	56.7%
Humerus	70.5%	67.3%
Elbow	68.7%	51.1%
Forearm	75.83%	59.8%
Hand	81.1%	77.2%
Shoulder	80.35%	69.88%
Wrist	86.6%	71.5%

TABLE 4. Accuracy obtain using three routing.

Image	Training accuracy	Validation accuracy
Finger	89.2%	72.4%
Humerus	92.43%	83.7%
Elbow	84.3%	78.87%
Forearm	87.6%	88.5%
Hand	93.6%	92.2%
Shoulder	91.7%	83.4%
Wrist	85.5%	79.87%

the data by increasing the c_{ij} value for a specific mother capsule. So to avoid overfitting we have decided to take four routing.

C. COHEN KAPPA SCORE COMPARISON

Cohen-kappa statistic is considered more robust in health care studies and in the case of musculoskeletal studies kappa statistic gives more valuable information [17], [18]. It measures inter-rater agreement for qualitative or categorical items. If there are two raters whom each classify N items into C mutually exclusive categories we can use Cohen's kappa

TABLE 5. Accuracy obtain using four routing.

Image	Training accuracy	Validation accuracy
Finger	98.3%	75.5%
Humerus	94.8%	81.2%
Elbow	88.12%	86.12%
Forearm	90.1%	89.11%
Hand	93.07%	91.09%
Shoulder	94.06%	92.08%
Wrist	96.04%	95.15%

TABLE 6. Kappa statistic score for MURA dataset using capsnet.

Image	Kappa score
Finger	.7351 (.9586,.5116)
Humerus	.754(.896,.61177)
Elbow	.7334(.7538,.713)
Forearm	.785(.795,.775)
Hand	.8351(.8557,.8145)
Shoulder	.8558(.87582,.8358)
Wrist	.90775(.9172,.8983)
Average	.80115(.8646,.7377)

TABLE 7. Kappa statistic score for MURA dataset using densenet.

Image	Kappa score
Finger	.389 (.446,.332)
Humerus	.6(.642,.558)
Elbow	.71(.745,.674)
Forearm	.737(.766,.707)
Hand	.851(.871,.83)
Shoulder	.729(.76,.697)
Wrist	.931(.94,.922)
Average	.705(.7,.71)

to measure the agreement between them. If P_o represents the relative observed agreement among raters which is identical to accuracy and P_e represents the hypothetical probability of chance agreement then the formula to calculate Cohen's kappa for two raters is:

$$\kappa = \frac{P_o - P_e}{1 - P_e} \tag{7}$$

Table 7 demonstrated the kappa score of densenet trained on MURA dataset [19]

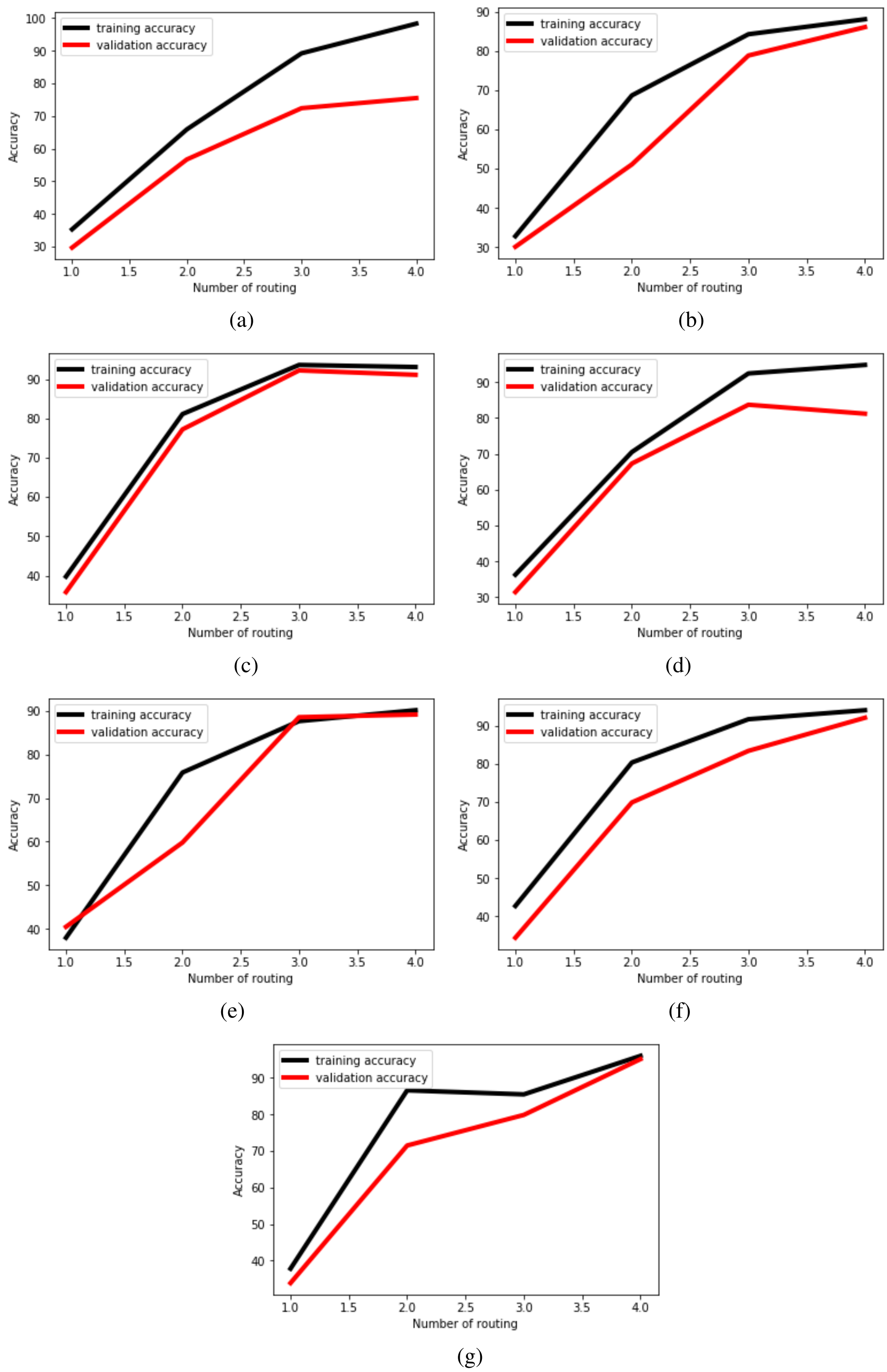


FIGURE 6. Training-Validation accuracy vs. Number of routing graph indicating that increasing the number of routing causes overfitting in the case of hand and humerus. (a) Finger. (b) Elbow. (c) Hand. (d) Humerus. (e) Forearm. (f) Shoulder. (g) Wrist.

From table 6 and 7 it is cleared that the proposed capsnet architecture provides almost 10% better kappa score than the 169 layers of densenet while using 50% less training data.

In fig.7 simultaneous plot of loss and accuracy for each epoch is given.

VII. FUTURE RESEARCH AREA

Capsule network has a very high potential in overcoming the limitations of CNN. Still now CNN is considered as one of the highly capable deep learning algorithm and is applied in various fields though it has some serious issues. To overcome

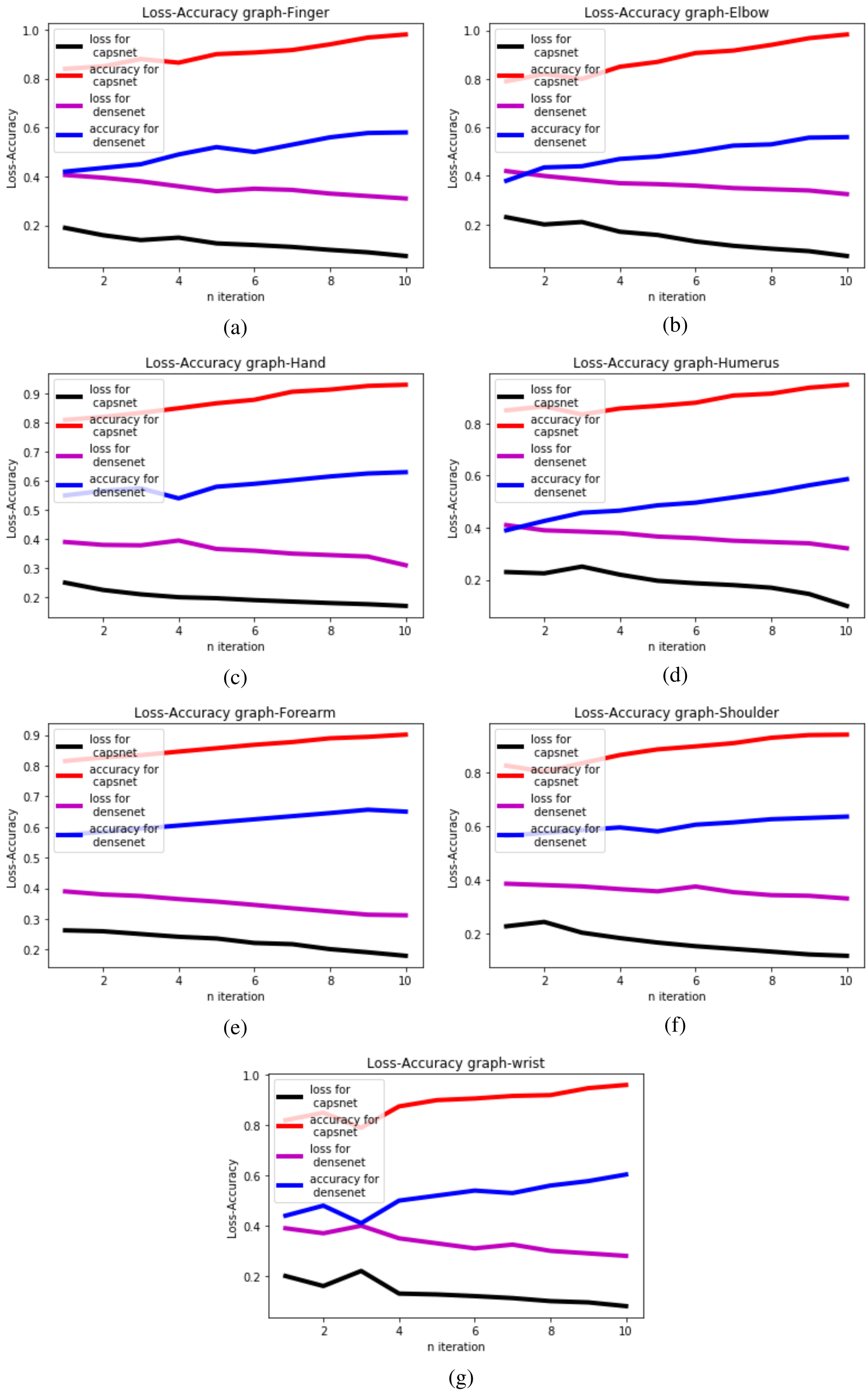


FIGURE 7. **Loss-Accuracy curve plotted against the number of iteration is showing the comparison between the densenet and capsnet and also indicating the improvement in accuracy and minimization of loss in every iteration. To compare both models randomly chosen 50% data were used to train both networks. (a) Finger. (b) Elbow. (c) Hand. (d) Humerus. (e) Forearm. (f) Shoulder. (g) Wrist.**

these issues of CNN, capsule network is a very good alternative architecture. Hence research in capsule network is very promising. As capsule network is a very recent idea, it has been used in very limitate areas like classification problem. Also musculoskeletal problem is already a matter of concern as more than 1.7 billion people are currently suffering from it. Hence accurate detection will help to go further diagnosis and treatment. Hence this is also a great area for future research.

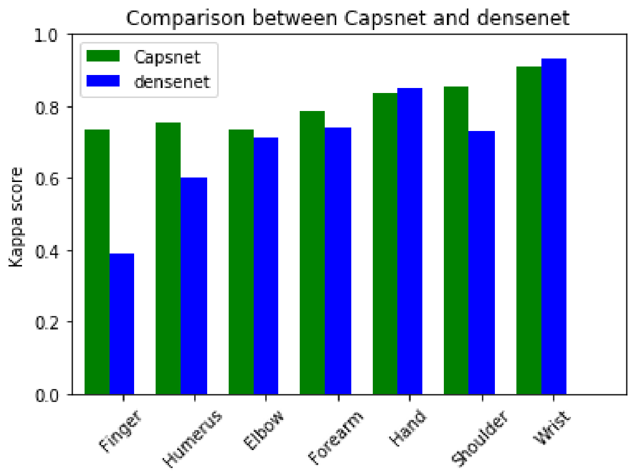


FIGURE 8. Comparison of Kappa score between Capsnet and densenet.

As we have used only 224 × 224 pixel size and only 50% of data for training the capsule network, we have a plan to use higher pixel size and more training data to train the model and analyze the results. Moreover, we want to use a deeper network and test the outcomes.

VIII. CONCLUSION

Proposed capsule network is capable of determining the abnormality in musculoskeletal radiography more accurately than 169 layer densenet. Also from the BRISQUE score and NIQE score it is cleared that accuracy increases when the resized image size is more close to the actual image size. Not only that, 50% less training data is used to train the network. As this network can perform well with a small number of data, it can also outperform CNN in such cases where a large amount of data cannot be provided.

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