Anomaly Detection using Capsule Networks for High-dimensional Datasets

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Abstract

Anomaly detection is an essential problem in machine learning. Application areas include network security, health care, fraud detection, etc., involving high-dimensional datasets. A typical anomaly detection system always faces the class-imbalance problem in the form of a vast difference in the sample sizes of different classes. They usually have class overlap problems. This study used a capsule network for the anomaly detection task. To the best of our knowledge, this is the first instance where a capsule network is analyzed for the anomaly detection task in a high-dimensional complex data setting. We also handle the related novelty and outlier detection problems. The architecture of the capsule network was suitably modified for a binary classification task. Capsule networks offer a good option for detecting anomalies due to the effect of viewpoint invariance captured in its predictions and viewpoint equivariance captured in internal capsule architecture. We used six-layered under-complete autoencoder architecture with second and third layers containing capsules. The capsules were trained using the dynamic routing algorithm. We created 10-imbalanced datasets from the original MNIST dataset and compared the performance of the capsule network with 5 baseline models. Our leading test set measures are F1-score for minority class and area under the ROC curve. We found that the capsule network outperformed every other baseline model on the anomaly detection task by using only ten epochs for training and without using any other data level and algorithm level approach. Thus, we conclude that capsule networks are excellent in modeling complex high-dimensional imbalanced datasets for the anomaly detection task.

Keywords: Anomaly Detection, Capsule Networks, Autoencoders, Dynamic Routing, Class Imbalance

1. Introduction

The problem of anomaly detection refers to the problem of finding patterns in data that do not conform to expected behavior, or simply anomaly detection is a method of detecting unusual behavioral patterns in a system. These anomalous behaviors have different names in domains like anomalies, outliers, discordant observations, exceptions, aberrations, surprises or contaminants, etc. Typically the anomalous items translate to some kind of problems such as bank fraud, a structural defect, medical problems, errors in a text, network intrusion, event detection in sensor network, or ecosystem disturbances Sommer and Paxson (2010). Anomalies are also referred as outliers, novelties, noise, deviations, and exceptions. Most of the time, in practical systems, we are interested in rarely occurring instances like network intrusion, defect in a machine in a large factory, credit card fraud, suspicious pat-
terns in a production process in a manufacturing environment, detecting ability to repay the loan of a regular customer by monitoring his/her financial behavior, etc. We are highly interested in those instances because of their huge impact on the entire system in their respective domains. Also, note that novelty detection and outlier detection are two different approaches in anomaly detection. The difference between them can be seen from below:

**Novelty Detection:** When training data is not polluted by outliers, and we are interested in detecting anomalies in the new observations. This concept is specially used by unsupervised algorithms such as autoencoders and one-class SVM (Schölkopf et al. (2001)).

**Outlier Detection:** When training data contains outliers, and we need a central tendency measure of the training data, ignoring the deviant observations. This concept is mainly used by all the supervised learning algorithms and unsupervised learning algorithms such as Isolation Forest (Liu et al. (2008)), Local outlier factor (Breunig et al. (2000), DBSCAN (Ester et al. (1996)), etc.

Basic requirement of an excellent anomaly detection system is that it must perform well for both novelty detection as well as outlier detection.

**Anomaly Detection Techniques**

Anomaly detection techniques can be broadly categorized into three categories: supervised learning methods, unsupervised learning methods, and semi-supervised learning methods. Some of the popular anomaly detection techniques used by now are distance-based techniques, density-based techniques (used by algorithms such as k-nearest neighbor, local outlier factor, isolation forest, etc.), Ensemble techniques, one-class learning methods, Bayesian networks, hidden Markov models, cluster-based outlier detection, fuzzy logic based outlier detection, Replicator neural networks, Autoencoders, Deviation from association rules and frequent itemsets, Subspace & correlation-based outlier detection.

The importance of anomaly detection is due to the fact that most of the time, anomalous instances in a system translate to the most critical information in a system. Cybercrime and threat activities have become a critical part of our daily life, and the importance of network security has continuously emerged as a significant concern Kwon et al. (2017). There is a wide range of domains in which anomaly detection plays a critical role. We can take the example of detection of abnormal behavior in crowded scenes where Sabokrou et al. (2018) used Fully Convolutional Neural Network (FCN) on temporal data. They transferred pre-trained FCN to unsupervised FCN to ensure the detection of global anomalies. Du et al. (2017) proposed DeepLog, a deep neural network utilizing Long Short-Term Memory (LSTM) to model system log as a natural language sequence. DeepLog records system states and significant events at various critical points to help debug system failures and perform root cause analysis. Lu et al. (2018) developed an anomaly detection system using reinforcement learning to prevent the motor of the drone from operating at abnormal temperatures. The proposed system automatically lands the drone once the temperature exceeds the threshold. Anomaly detection is also used in malware detection in computer programs, Kharche and Thakare (2015) proposed a general worm detection model where they used Bayesian Network, decision tree, and random forest classifiers in their model.

Nowadays, deep learning models are getting more and more popular in anomaly detection tasks due to their superior performance compared to other classical machine learn-
Capsule Network for Anomaly Detection

An and Cho (2015) proposed variational autoencoder-based anomaly detection using reconstruction probability which outperformed earlier autoencoder and principle components based anomaly detection methods. Zhou and Paffenroth (2017) proposed a more Robust Deep Autoencoder(RDA) architecture for eliminating noise and outliers without needing to access the clean data. Their model was inspired by Robust Principal Component Analysis, where they split the data $X$ into two parts, $X = L_D + S$, where $L_D$ is effectively reconstructed by deep autoencoder $S$ contains the outliers and the noise in the original data $X$. This method showed significant improvement of 73% over Isolation Forests. Deecke et al. (2018) showed that searching the latent space of the generator of Generative Adversarial Network(GAN) can be leveraged for use in anomaly detection tasks. They achieved state-of-the-art performance on standard image benchmark datasets. Their model can be used for the unsupervised anomaly detection task. Schlegl et al. (2017) used GANs for unsupervised anomaly detection to guide marker discovery. Zong et al. (2018) proposed a deep autoencoding Gaussian mixture model for unsupervised anomaly detection. They outperformed state-of-the-art anomaly detection techniques on high-dimensional datasets. Zenati et al. (2018) used efficient GAN-based anomaly detection methods and achieved state-of-the-art performance while being several hundred-fold faster at test time than the recently published GAN-based method back then. Ngo et al. (2019) proposed a new GAN architecture called fence GAN (FGAN) with modified GAN loss. FGAN directly uses the discriminator score as an anomaly threshold. Li et al. (2019) did multivariate anomaly detection on time series data using GANs and named their model as MAD-GAN.

Class Overlap Problem in Anomaly Detection

When the anomalous instances occur in very dense sub-spaces occupied mostly by standard instances, then in these scenarios, machine learning algorithms cannot detect those minority classes or require a highly complex algorithm to detect them. This problem is called the class overlap problem in machine learning Bellinger et al. (2017). In simple words, when a small cluster of minority class instances lies inside a dense cluster of majority class instances in latent spaces, the poor performance of learning algorithms on minority classes is due to the class overlap problem. Most of the time, this problem occurs when the dataset is missing some essential features or due to improper handling of data. This problem is common in non-image datasets.

2. Capsule Networks

Geoffrey Hinton introduced the idea of capsules in a neural network, then Sabour et al. (2017) introduced an entirely new type of neural network based on capsules. They provided six-layered autoencoder-based architecture having a capsule layer in the encoder part. They published an algorithm called dynamic routing between capsules that allowed to train such a network. The main characteristic of this network is the viewpoint invariance for the detection of classes due to viewpoint equivariance captured by internal capsule architecture. It allows this network to correctly label unobserved patterns with very high probability. This network is more robust for unobserved anomalous and normal instances. Later they provided improved architecture of capsule net (Hinton et al. (2018)) where they used a pose
matrix for each capsule instead of a vector in the earlier model. For the routing of capsules in the network, they used Expectation-Maximization (EM) algorithm. On the smallNORB benchmark dataset, this model reduced the test errors by 45% compared to the state-of-the-art. They also showed that the capsule network is robust against the white box adversarial attacks, which seems to be promising for their application in anomaly detection problems.

2.1. Why Capsule Networks for Anomaly Detection

Capsule Network was initially proposed to better mimic the biological neural organization by overcoming the drawbacks present in Convolutional Neural Networks (CNN). In CNNs, pooling allows a degree of translational invariance and a large number of feature types to be represented. Capsule theory argues that pooling in CNNs violates biological shape perception and ignores the underlying linear manifold in images. Pooling also causes loss of important information by throwing out data, thus damaging nearby feature detectors. The biggest advantage of capsule networks is that it provides equivariance in internal architecture (trained capsules) while, on the other hand, CNNs provide invariance due to discarding positional information.

The aim of capsules is to use underlying linearity to deal with viewpoint variations and improve segmentation decisions. Capsules use high dimensional coincidence filtering. Zhou et al. (2016) used spatial-temporal CNNs for anomaly detection and localization in crowded scenes and outperformed state-of-the-art methods. Considering the advantages of capsule networks over CNNs, they appear to be excellent candidates for the anomaly detection task. We know that anomalies are few and different from normal instances in a system. Most of the time, newer anomalies follow completely new unobserved patterns occurring in a system. Since Sabour et al. (2017) already shown that capsule networks have excellent viewpoint invariance properties for detecting the class of an instance, and also they have viewpoint equivariance property in the internal architecture due to the presence of the capsules, they can model unobserved patterns better as compared to CNNs and other present state-of-the-art methods. Another advantage of capsules networks is that they require fewer data to achieve the same performance as other deep learning models. So if we are not performing unsupervised anomaly detection, then capsule networks are a good choice due to the scarcity of anomalous instances in the training set. Also, using them as supervised learning methods and having their considerably better ability for classifying highly overlapped instances (Sabour et al. (2017)), they solve the class overlap problem which unsupervised learning models could not solve.

The better ability of capsule networks for the class overlap is that the parallel attention mechanism of this network allows each capsule at one level to attend to some active capsules at the level below and ignore others. So when multiple objects are present in an instance, active lower level capsules send their outputs to their respective parent capsules. So multiple parent capsules become active, and the process goes on till the output layer has multiple capsules indicating the presence of a class. So due to all these facts, we believe that capsule networks are an excellent choice for anomaly detection.
3. Capsule Network Architecture for anomaly detection

We used six-layered autoencoder architecture containing two layers of capsules similar to the one proposed in Sabour et al. (2017). The network has two parts, an encoder and a decoder having three layers each. The network’s input layer takes 28x28 pixel images of the MNIST dataset. The first hidden layer is a convolution layer that outputs a tensor of size 20x20x256 using ReLu activation and without padding.

The second hidden layer was the first layer containing capsules, outputs a tensor of size 6x6x8x32. The output of the second layer can be viewed as 6x6x32 8-dimensional capsules. The third layer of the network is also the output layer of the encoder, and the second capsule layer of the network, outputs two 16-dimensional vectors, one for each class. Here at the place of two capsules, we could have taken one capsule only because the length of the capsule represents the presence of a class, and we are dealing with binary classification here. Nevertheless, as per capsule theory, each capsule’s instantiation parameters should be recording one class because allowing a capsule to record more than one class’s instantiation parameters may induce high bias in the network. Due to this, we kept a second capsule for recording anomalous instances. However, the size of the second capsule depends upon the imbalance and nature of anomalies in the data, which is a part of another discussion.

The decoder part of the network has three fully connected layers outputting a number of neurons as 512,1024, and 784, respectively. The output of the decoder is then reshaped back to size 28x28 to see the reconstructed image.

The loss function of the encoder of this network is very similar to the SVM loss function. Here is the loss function for the encoder part:

\[ L_c = T_c (\max(0, m^+ - \|v_c\|)^2) + \lambda (1 - T_c) (\max(0, \|v_c\| - m^-)^2) \]

Here, \( L_c \) is loss term for one DigitCap. \( v_c \) is DigitCap vector. \( T_c \) is 1 for correct digitcap and 0 for incorrect digitcap, basically this represent true label of an instance. \( \lambda \) is a constant they originally used for numerical stability. \( m^+ \) and \( m^- \) are constants which are fixed at 0.9 and 0.1 respectively. The loss function for decoder (reconstruction loss) is simply the mean squared error let it denote by \( L_d \). So the loss function for entire network is as follows:

\[ L = \sum_c L_c + \alpha L_d \]
So in the total loss, reconstruction loss acts as a regularizer whose strength is controlled using parameter \( \alpha \).

4. Experiments and discussion

4.1. Data description

The experiments were performed on standard MNIST data (LeCun and Cortes (2010)). The training set of this data contains 60000, 28x28 pixel images of handwritten digits from 0 to 9. The test set of this data contains 10000 images of the same size. A validation set of 5000 images was prepared using stratified random sampling from training data. Inherently this is not highly imbalanced data. Since our objective is to assess the performance of capsule network for anomaly detection task, we have made this data imbalanced and converted it to binary classification problem from multi-class classification problem. We created 10 subsets for each training, validation, and test dataset. These 10 subsets correspond to each of the 10 classes. For example, for training subset-0, we took all the samples belonging to class 0 from training data, randomly sampled instances from other classes from the same training data, and labeled them all as 1. For each subset, we labeled the majority class or normal class as 0 and the class of anomalous instances as 1. The number of sampled instances from other classes (anomalous instances) was kept around \( 1/10 \)th of the number of instances of class 0.

Similarly, validation subset-0 and test subset-0 were created. So there were 10 training subsets, 10 validation, and 10 test subset corresponding to each class where the subset number indicates which class is in the majority in the dataset. So we created 10 binary class imbalanced datasets from MNIST data to evaluate the performance of our capsule network on anomaly detection task.

4.2. Baseline Methods

We considered traditional, popular, and state-of-the-art anomaly detection methods.

- **Random Forest Classifier**: This is a popular ensemble learning decision tree-based method proposed by Breiman (2001). This method performs very well most of the time for supervised learning tasks. We tuned its important parameters during training, like the number of trees in the forest and the minimum number of samples required at a node for the further split. We also enabled cost-sensitive learning by tuning class weight parameters.

- **XGBoost Classifier**: XGBoost is a tool proposed by Friedman (2001) and motivated by formal principles of machine learning, mathematical optimization, and computational efficiency of learning algorithms. Due to its recent success in many machine learning-based competitions held on Kaggle and other platforms, we also decided to include this model for comparative analysis. We kept the base classifier of this model as gradient boosted trees and tuned the learning rate, number of base estimators, minimum child weight, and \( \gamma \) hyperparameters.

- **Deep Neural Network**: We used six layers deep neural network architecture with \( \text{relu} \) activation function for hidden layers and sigmoid activation function for the
Capsule Network for Anomaly Detection

Figure 2: F1-Score of Capsule Network and baseline models on test datasets for the minority class

output layer. The number of hidden units in each layer was also tuned along with activation functions.

- **Isolation Forest Classifier:** This is an unsupervised learning method for outlier detection proposed by Liu et al. (2008). This is one of the newest techniques to detect anomalies. This algorithm is based on the isolation mechanism according to which anomalies can be isolated much earlier than a normal instance due to their very different nature than normal instances. We tuned a number of the base estimator and maximum features to draw from training set hyper-parameters.

- **Undercomplete Deep Autoencoder:** We used six-layered undercomplete deep autoencoder architecture, three layers each for encoder and decoder part. We used the concept of reconstruction probability for binary classification in our case. Hidden layer sizes and activation functions were fully tuned. For classification, we used reconstruction probability similar to An and Cho (2015).

4.3. Results

We evaluated the performance of capsule network and baseline methods on all the 10 imbalanced datasets created from the MNIST dataset as described earlier. We kept the F1-score for minority class as the main evaluation metric and Area Under ROC (AUROC) and overall accuracy. For the Dataset-0, we observed the following results:

Clearly, in table 1, we can observe that on dataset-0, the capsule network is outperforming every other baseline model. The same can also be observed from figure 2 given below.
| Models            | Accuracy | AUROC | Precision | Recall | F1-score |
|------------------|----------|-------|-----------|--------|----------|
| Random Forest    | 98.84%   | 0.988 | 0.96      | 0.94   | 0.95     |
| XGBoost          | 98.30%   | 0.994 | 0.97      | 0.89   | 0.93     |
| DNN              | 97.22%   | 0.996 | 0.97      | 0.80   | 0.88     |
| Isolation Forest | 97.62%   | 0.680 | 0.73      | 0.38   | 0.50     |
| Autoencoder      | 85.67%   | 0.892 | 0.45      | 0.72   | 0.55     |
| Capsule Network  | 99.47%   | 0.999 | 1.00      | 0.96   | 0.98     |

Table 1: The test set results for Dataset-0 (Precision, recall, and f1-score are for minority class)

Apart from results on dataset-0, we saw that the capsule network outperformed every other baseline model on all the remaining datasets (from dataset-1 to dataset-9), which can be seen from Appendix A and Appendix B. Capsule network is shown superior results for all evaluation metrics used here, which are F1-score, AUROC, and accuracy. Since the data is high-dimensional, reasonably complex, and imbalanced, we can say that the capsules network could model this data really well, which supports our arguments made in section 2.1. So we have observed that capsules networks have a high potential to model complex high-dimensional imbalanced data compared to other popular anomaly detection models. In the present study, we used dynamic routing-based capsules in our network, which is an encouraging sign to go for expectation-maximization-based capsules networks (Hinton et al. (2018)).
5. Conclusion

Anomaly detection is the problem of detecting unexpected, unusual behavioral patterns in a system. In this domain, we deal with highly imbalanced datasets. We have seen that supervised machine learning algorithms like Random forest, XGBoost, deep neural networks, and unsupervised learning models like isolation forest, one-class SVM, and autoencoders perform well for low dimensional data. We also use data level approaches like undersampling and oversampling, algorithm level approaches like cost-sensitive learning, and different calibration techniques to improve the results. However, these algorithms struggle most of the time on high-dimensional complex data.

Sabour et al. (2017) and Hinton et al. (2018) shown that capsule networks are excellent in modeling viewpoint invariance in predictions due to viewpoint equivariance captured by internal capsule architecture. This encouraged us to use capsule networks for anomaly detection tasks where viewpoint invariance and viewpoint equivariance play an essential role. We conducted our results on imbalanced MNIST datasets created from original MNIST data (LeCun and Cortes (2010)). We used random forest, XGBoost, deep neural network, isolation forest, and undercomplete deep autoencoder as our baseline models to compare the performance of capsule network on this data. We observed that for training up to 10 epoch only, the capsules network outperformed every other baseline model on all high-dimensional datasets we created from MNIST data. We can conclude that capsule networks are excellent in modeling complex high-dimensional imbalanced datasets from these results.

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### Appendix A. First Appendix

Experimental results on MNIST dataset. The values of precision, recall, and f1-score are for minority class which is of our interest. We kept Accuracy and AUROC results to get the overall performance of classifiers for both classes.

| Models         | Accuracy | AUROC  | Precision | Recall | F1-score |
|----------------|----------|--------|-----------|--------|----------|
| Random Forest  | 95.81 %  | 0.986  | 0.81      | 0.85   | 0.83     |
| XGBoost        | 95.89 %  | 0.993  | 0.94      | 0.69   | 0.80     |
| DNN            | 97.21 %  | 0.996  | 0.99      | 0.77   | 0.87     |
| Isolation Forest | 88.75 %  | 0.624  | 0.56      | 0.28   | 0.37     |
| Autoencoder    | 83.78 %  | 0.768  | 0.38      | 0.54   | 0.44     |
| Capsule Network | **99.13 %** | **0.999** | **1.00** | **0.93** | **0.96** |

Table 4: Test set results for Dataset-3
| Models         | Accuracy | AUROC | Precision | Recall | F1-score |
|----------------|----------|-------|-----------|--------|----------|
| Random Forest  | 96.58 %  | 0.988 | 0.80      | 0.94   | 0.87     |
| XGBoost        | 95.89 %  | 0.993 | 0.94      | 0.69   | 0.80     |
| DNN            | 98.20 %  | 0.998 | 0.95      | 0.89   | 0.92     |
| Isolation Forest | 88.11 % | 0.60  | 0.48      | 0.23   | 0.31     |
| Autoencoder    | 74.17 %  | 0.730 | 0.26      | 0.64   | 0.37     |
| Capsule Network | 99.58 % | 0.999 | 0.99      | 0.97   | 0.98     |

Table 3: Test set results for Dataset-2

| Models         | Accuracy | AUROC | Precision | Recall | F1-score |
|----------------|----------|-------|-----------|--------|----------|
| Random Forest  | 96.51 %  | 0.985 | 0.86      | 0.85   | 0.86     |
| XGBoost        | 97.14 %  | 0.991 | 1.00      | 0.77   | 0.87     |
| DNN            | 97.94 %  | 0.988 | 0.98      | 0.85   | 0.91     |
| Isolation Forest | 89.99 % | 0.680 | 0.65      | 0.39   | 0.49     |
| Autoencoder    | 86.77 %  | 0.834 | 0.47      | 0.64   | 0.54     |
| Capsule Network | 99.28 % | 0.999 | 1.00      | 0.94   | 0.97     |

Table 4: Test set results for Dataset-4

| Models         | Accuracy | AUROC | Precision | Recall | F1-score |
|----------------|----------|-------|-----------|--------|----------|
| Random Forest  | 97.37 %  | 0.995 | 0.96      | 0.84   | 0.89     |
| XGBoost        | 95.33 %  | 0.993 | 0.99      | 0.66   | 0.79     |
| DNN            | 98.25 %  | 0.997 | 0.98      | 0.89   | 0.93     |
| Isolation Forest | 86.49 % | 0.554 | 0.47      | 0.13   | 0.21     |
| Autoencoder    | 80.17 %  | 0.827 | 0.37      | 0.73   | 0.50     |
| Capsule Network | 99.32 % | 0.999 | 0.99      | 0.96   | 0.97     |

Table 5: Test set results for Dataset-5

| Models         | Accuracy | AUROC | Precision | Recall | F1-score |
|----------------|----------|-------|-----------|--------|----------|
| Random Forest  | 97.90 %  | 0.996 | 0.91      | 0.92   | 0.92     |
| XGBoost        | 98.08 %  | 0.997 | 0.95      | 0.89   | 0.92     |
| DNN            | 98.36 %  | 0.997 | 0.96      | 0.91   | 0.93     |
| Isolation Forest | 87.76 % | 0.633 | 0.52      | 0.31   | 0.39     |
| Autoencoder    | 87.76 %  | 0.877 | 0.51      | 0.68   | 0.58     |
| Capsule Network | 99.18 % | 0.999 | 0.98      | 0.96   | 0.97     |

Table 6: Test set results for Dataset-6

Table 7: Test set results for Dataset-6
## Capsule Network for Anomaly Detection

| Models            | Accuracy | AUROC | Precision | Recall | F1-score |
|-------------------|----------|-------|-----------|--------|----------|
| Random Forest     | 95.19 %  | 0.989 | 0.73      | 0.95   | 0.82     |
| XGBoost           | 97.08 %  | 0.996 | 0.96      | 0.79   | 0.86     |
| DNN               | 98.02 %  | 0.996 | 0.96      | 0.87   | 0.91     |
| Isolation Forest  | 92.27 %  | 0.766 | 0.72      | 0.56   | 0.63     |
| Autoencoder       | 93.22 %  | 0.923 | 0.72      | 0.70   | 0.71     |
| Capsule Network   | **98.88 %** | **0.999** | 0.98      | 0.92   | **0.95** |

Table 8: Test set results for Dataset-7

| Models            | Accuracy | AUROC | Precision | Recall | F1-score |
|-------------------|----------|-------|-----------|--------|----------|
| Random Forest     | 95.05 %  | 0.982 | 0.80      | 0.80   | 0.80     |
| XGBoost           | 94.15 %  | 0.989 | 0.99      | 0.53   | 0.69     |
| DNN               | 95.32 %  | 0.992 | 1.00      | 0.62   | 0.77     |
| Isolation Forest  | 87.22 %  | 0.582 | 0.46      | 0.20   | 0.28     |
| Autoencoder       | 61.21 %  | 0.656 | 0.19      | 0.67   | 0.30     |
| Capsule Network   | **98.65 %** | **0.996** | 1.00      | 0.89   | **0.94** |

Table 9: Test set results for Dataset-8

| Models            | Accuracy | AUROC | Precision | Recall | F1-score |
|-------------------|----------|-------|-----------|--------|----------|
| Random Forest     | 94.42 %  | 0.975 | 0.75      | 0.80   | 0.77     |
| XGBoost           | 95.03 %  | 0.983 | 0.95      | 0.61   | 0.75     |
| DNN               | 97.38 %  | 0.991 | 0.95      | 0.82   | 0.88     |
| Isolation Forest  | 89.44 %  | 0.675 | 0.59      | 0.39   | 0.47     |
| Autoencoder       | 90.22 %  | 0.912 | 0.57      | 0.72   | 0.64     |
| Capsule Network   | **98.25 %** | **0.998** | 0.99      | 0.86   | **0.92** |

Table 10: Test set results for Dataset-9

### Appendix B. Second Appendix

Here are the plots of the results obtained on test data of different models used here:
Figure 4: Accuracies of Capsule Network and baseline models on test datasets