Enhancing IoT Security: Anomaly Detection using Deep Support Vector Data Description and Contractive Autoencoder

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Introduction & Motivation

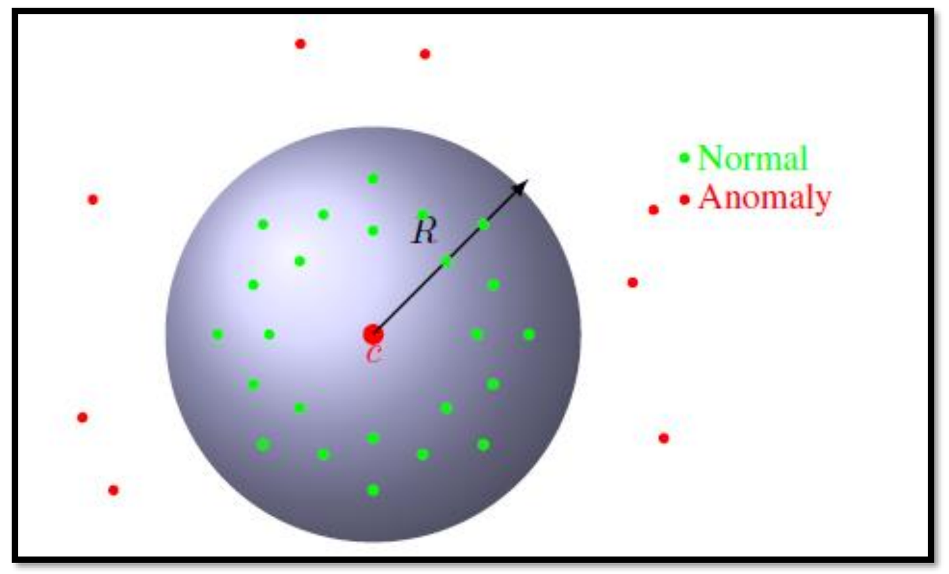
- ❑ **IoT security challenge:** Detecting diverse, heterogeneous attacks, both known and novel
- ❑ Current models struggle with handling heterogeneity and lack dedicated anomaly detection objectives
- ❑ **Our solution:** Integrating DSVDD with Contractive Autoencoders (CAE), with an objective function based on anomaly detection
- ❑ Outperforms traditional AI in subtle anomaly detection

Methodology

- ❑ Combined Deep Support Vector Data Description (DSVDD) with Contractive Autoencoders (CAE)
- ❑ CAE learns robust, low-dimensional features from normal data
- ❑ DSVDD identifies anomalies outside a minimal hypersphere in feature space[1]
- ❑ Semi-supervised learning using only normal data for training
- ❑ Threshold optimized using F-score on validation set
- ❑ Objective Function:

$$J_{DSVDD-CAE}(\theta) = J_{CAE}(\theta) + \alpha J_{DSVDD}(\theta)$$

Methodology



Visualization of SVDD hypersphere with normal and anomalous data points.

Algorithm 1 Anomaly Detection using DSVDD-CAE

```
function PREDICT(xtrain, xtest, xval, yval)
    score-normal ← ComputeAnomalyScore(xtrain)
    threshold ← GetOptimalThreshold(xval, yval, score-normal)
    anomaly score ← ComputeAnomalyScore(xtest)
    is anomaly ← anomaly score ≥ threshold
    return is anomaly
function GETOPTIMALTHRESHOLD(xval, yval, score-normal)
    Define a range of potential_thresholds from min(score-normal) to max(score-normal)
    best_f1 ← 0
    best_threshold ← potential_thresholds[0]
    for each threshold in potential_thresholds do
        Predict anomalies for xval based on current threshold to get predicted_yval
        Compute F1 score using actual yval and predicted_yval
        if current F1 score > best_f1 then
            Update best_f1 and best_threshold with current F1 score and threshold
    return best_threshold
function COMPUTEANOMALYSCORE(x)
    z ← EncodeInput(x)
    distance ← ComputeDistance(z)
    x recon ← DecodeInput(z)
    recon error ← ComputeReconstructionError(x recon, x)
    anomaly score ← CombineScores(distance, recon error)
    return anomaly score
```

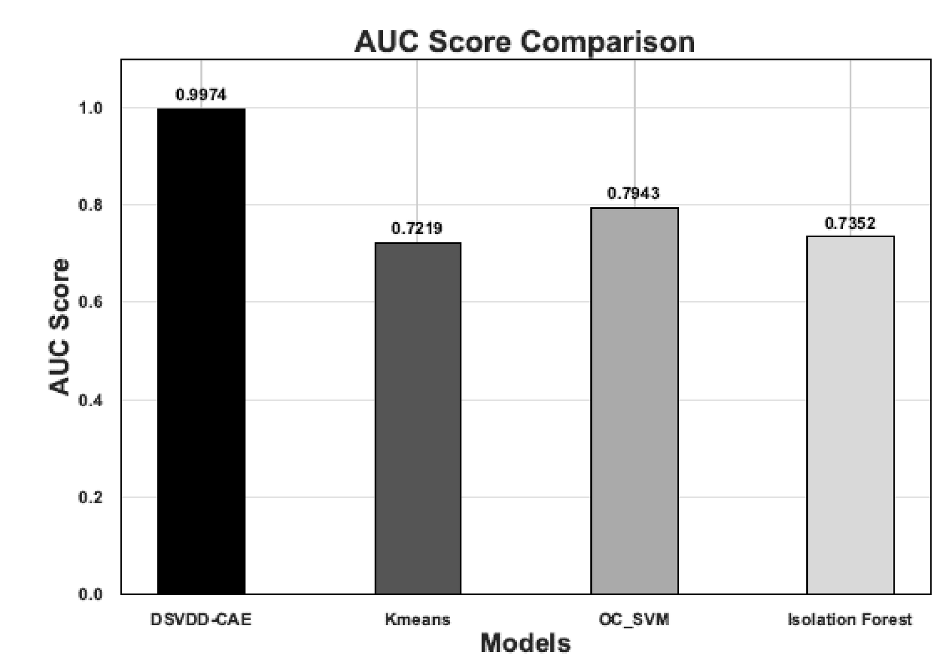
Results

Method	Precision	Recall	F1-score	Accuracy
KMeans	66.13%	66.16%	66.15%	87.81%
OCSVM	69.40%	69.43%	69.41%	88.98%
Isolation Forest	70.51%	68.95%	69.68%	89.50%
Proposed Method	**98.25%**	**99.80%**	**99.01%**	**99.64%**

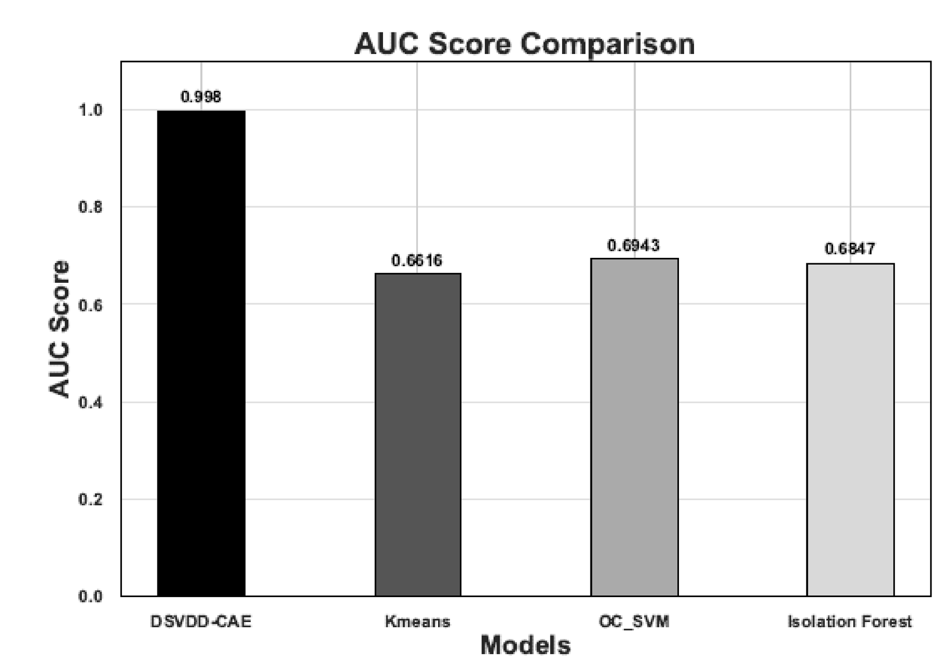
IoTID20 dataset

Method	Precision	Recall	F1-score	Accuracy
KMeans	84.77%	72.19%	76.28%	88.92%
OCSVM	91.34%	76.38%	81.35%	91.29%
Isolation Forest	86.86%	83.52%	77.89%	89.68%
Proposed Method	**98.77%**	**99.74%**	**99.25%**	**99.57%**

ToN-IoT dataset

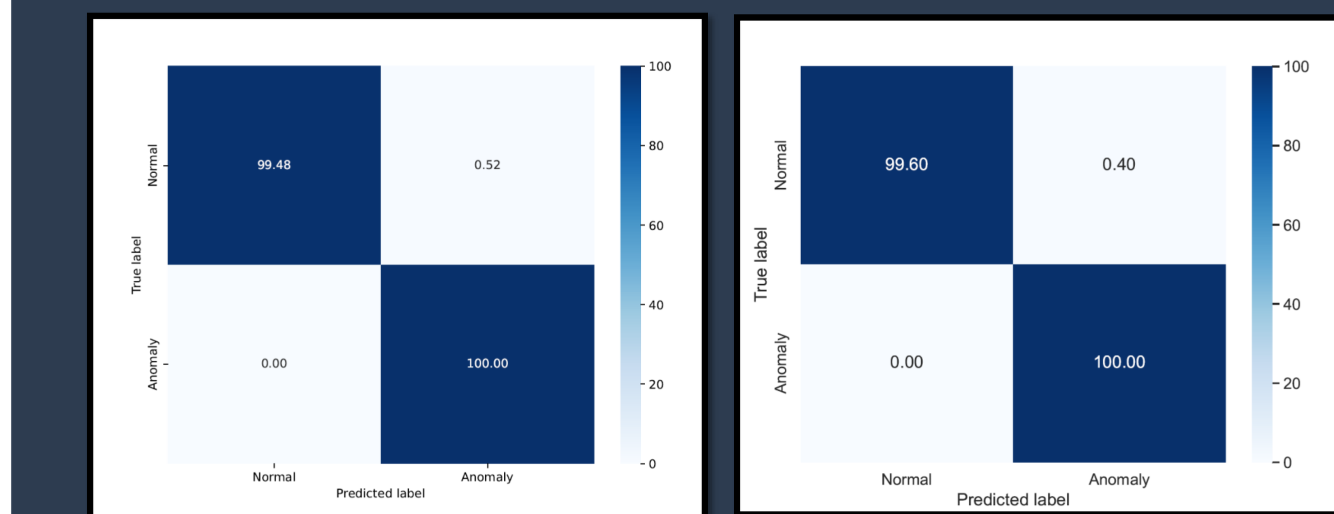


(a) AUC Score Comparison (TON-IoT dataset)



(b) AUC Score Comparison (IoTID20 Dataset)

Results



Confusion Matrices on ToN-IoT and IoTID20 Datasets

Conclusion

- ❑ **Proposed DSVDD-CAE model** for anomaly detection in IoT networks
- ❑ Achieved a **99.25%** F1-score on the ToN-IoT[2] dataset and a **99.01%** F1-score on the IoTID20[3] dataset, outperforming traditional methods
- ❑ **Future work:** Expand testing on additional IoT datasets to further assess generalization and model scalability

References

[1] Tax, D.M., Duin, R.P. Support Vector Data Description. Machine Learning 54, 45–66 (2004). https://doi.org/10.1023/B:MACH.0000008084.60811.49

[2] N. Moustafa. (2020). TON-IoT Dataset. [Online]. Available:https://cloudstor.aarnet.edu.au/plus/s/ds5zW91vdgjEj9i

[3] Ullah, Imtiaz and Mahmoud, Qusay H., A scheme for generating a dataset for anomalous activity detection in iot networks, Canadian Conference on Artificial Intelligence, Springer International Publishing, 2020.

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