

Efficient IOT Predictive Analytics Via Cloud-Integrated Auto encoder Capsule Networks

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Abstract

Cloud computing provides on-demand computing resources through the internet, while predictive analytics uses historical data and machine-learning methods to forecast outcomes. This paper presents a Polynomial Regressive Robust Autoencoded Deep Capsule Network (PRRA-CapsNet) for efficient predictive analytics in an IoT-enabled cloud environment. The model combines data acquisition, preprocessing, robust autoencoder feature selection, deep capsule classification and fine-tuning. Polynomial predictive mean imputation handles missing values, Modified Z-Score removes outliers, and the Azadkia–Chatterjee dependence coefficient supports relevant-feature selection. The class capsule layer applies Kulczynski similarity, and a wild horse herd optimization procedure fine-tunes the model. Experiments use the Global Air Pollution Dataset containing 23,463 instances and 12 attributes. Reported results show higher accuracy, precision, recall and F1-score, together with lower RMSE, MAE and prediction time than TRANS_GRU and MSTVFFN.

Keywords

IOT, Cloud Computing, Predictive Analytics, Deep Capsule Network, Robust Auto encoder, Feature Selection, Kulczynski Similarity, Air Pollution.

1. Introduction

Cloud computing delivers storage, processing, networking, databases and software through the internet. An IoT-enabled cloud environment extends this model by

collecting continuous data through connected sensors and transmitting the data to cloud servers for storage and analysis. This combination supports smart farming, healthcare, environmental monitoring and smart-city applications.

Predictive analytics is important when large volumes of sensor and environmental data must be converted into useful decisions. Existing air-pollution prediction approaches have reported limitations related to accuracy, scalability, generalization, feature selection, computational complexity and prediction time. The source paper reviews Transformer-GRU, multiscale spatial-temporal fusion, BiLSTM, LSTM, CNN-BiLSTM, sparse transformers, autoencoders and other models.

PRRA-CapsNet addresses these issues by integrating preprocessing, dimensionality reduction, capsule-based classification and optimization in a single workflow. The objective is to retain useful information while removing irrelevant features and reducing prediction overhead.

- IOT-aware cloud predictive analytics architecture.
- Polynomial predictive mean imputation and Modified Z-Score preprocessing.
- Robust autoencoder feature selection using the Azadkia–Chatterjee dependence coefficient.
- Kuleczynski similarity-based classification in the class capsule layer.
- Wild horse herd optimization for fine-tuning model weights.

2. Related Works

The reviewed literature contains deep-learning and machine-learning models for air-pollution prediction. TRANS GRU improves prediction accuracy but shows limitations on larger datasets. MSTVFFN predicts multiple pollutants but requires improved sensitivity and tuning. Other approaches use spatiotemporal attention, BiLSTM, LSTM, Gaussian process regression, GANs, CNN-based models and sparse transformers.

The recurring gaps identified in the source paper include insufficient computational-efficiency improvement, limited feature-selection mechanisms, restricted generalization across locations, high prediction time and incomplete hyper parameter optimization. Some approaches also require stronger treatment of missing and outlier values.

3. Proposed Methodology

The PRRA-CapsNet framework is designed to perform efficient predictive analytics in cloud computing environments. The architecture consists of four major stages: data acquisition, preprocessing, feature selection, and classification.

Initially, IOT sensors collect environmental information from multiple locations. These data samples are transmitted to the cloud server for storage and analysis. The collected dataset is then passed to the preprocessing stage. During preprocessing, missing values are estimated using polynomial predictive mean imputation. Outlier samples are detected and removed through the modified Z-score technique. This process improves the quality of the dataset and reduces noise.

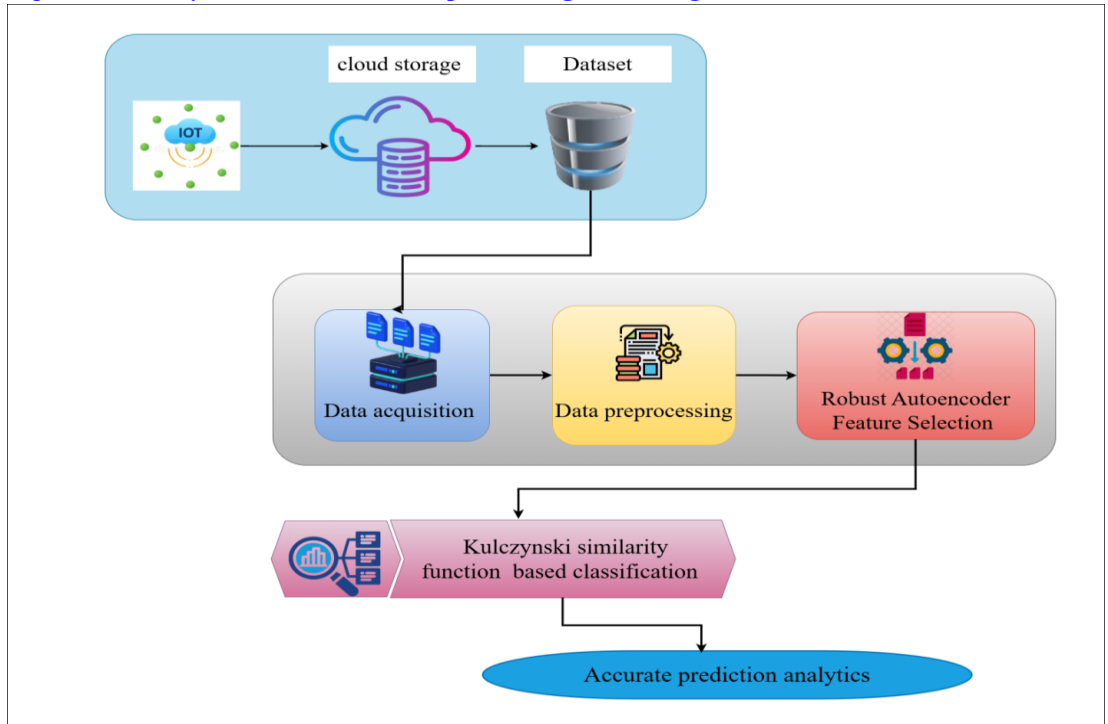


Figure 1. Architecture of the proposed PRRA-CapsNet model

After preprocessing, a robust autoencoder performs feature selection. The encoder transforms the high-dimensional input into a compact latent representation, while the decoder reconstructs the original data. The autoencoder identifies relevant features and removes redundant attributes. This dimensionality reduction process decreases computational overhead and enhances prediction performance.

The selected features are then provided to the class capsule layer. Capsule networks capture spatial relationships between features more effectively than traditional neural networks. The proposed model employs the Kulczynski similarity function to measure similarity between training and testing samples for accurate classification. To minimize classification error, the network parameters are optimized using a wild horse herd optimization algorithm. The optimization process iteratively updates weight values to achieve better prediction accuracy and lower false prediction rates.

3.1 ROBUST AUTOENCODER FEATURE SELECTION

Feature selection reduces the number of attributes supplied to the prediction stage. The robust auto encoder contains encoder and decoder functions. The encoder maps preprocessed input into a lower-dimensional latent representation, while the decoder reconstructs the input.

The Azadkia–Chatterjee dependence coefficient is used to evaluate the relationship between features and the target. A value closer to 1 indicates stronger dependence, while a value closer to 0 indicates weaker dependence. Relevant features are retained and unrelated features are removed.

According to the experimental results, seven essential features are selected from the original twelve attributes. This reduction is intended to lower dimensionality, remove redundancy and improve computational efficiency.

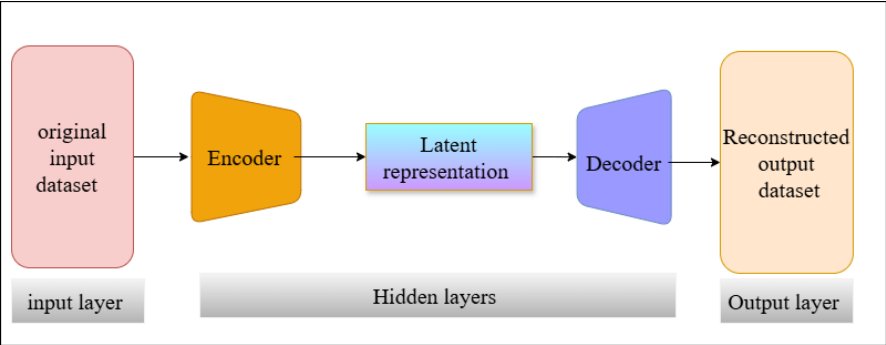


Figure 2. Robust autoencoder structure.

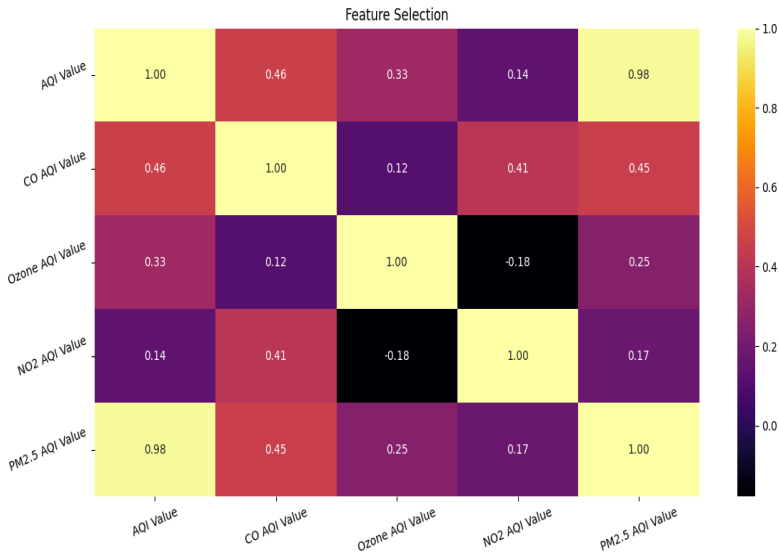


Figure 3. Feature correlation heatmap.



Figure 4. Seven selected relevant features.

4. IMPLEMENTATION RESULTS

The implementation follows data acquisition, preprocessing, feature selection and classification. After missing-value treatment and outlier removal, the robust auto encoder identifies seven important features. The selected features are then used by the deep capsule classifier.

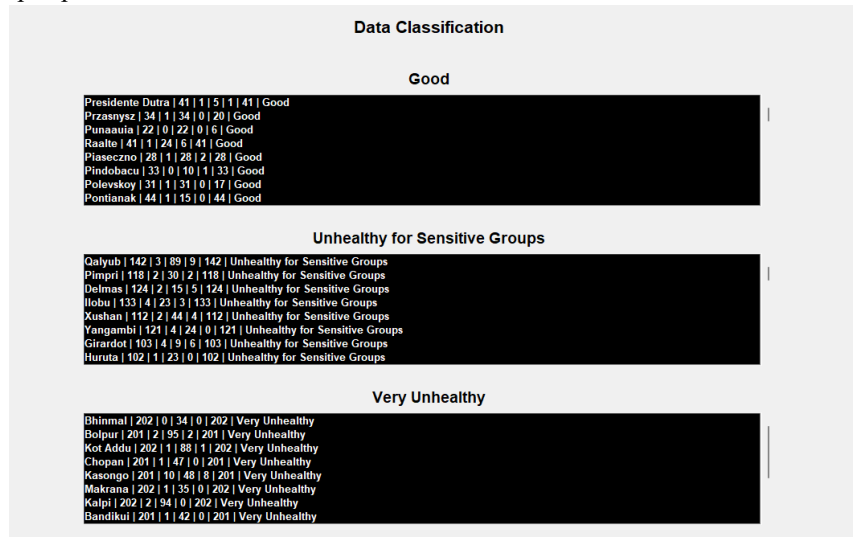


Figure 5. Prediction/classification outcomes.

Stage	Result	Purpose
Data acquisition	23,463 records; 12 attributes	Collect input data
Missing-value handling	Cleaned dataset	Complete observations
Outlier removal	1,341 KB refined size	Remove abnormal observations
Feature selection	7 relevant features	Reduce dimensionality
Classification	AQI categories	Generate prediction
Fine-tuning	Optimized weights	Reduce error

The source paper reports prediction of Good, Moderate, Unhealthy, Very Unhealthy and Hazardous categories using the seven selected features and Kulczynski similarity in the deep capsule network.

5. DISCUSSION AND CONCLUSION

The reported results consistently favor PRRA-CapsNet across accuracy, precision, recall, F1-score, RMSE, MAE and prediction time. The integrated preprocessing stage

improves data quality, robust autoencoder selection reduces the feature space, and the deep capsule network performs classification using the selected features.

The use of Kulczynski similarity supports training-testing sample comparison, while wild horse herd optimization searches for improved weights. These combined stages are associated in the source paper with higher predictive performance and lower computational cost.

Conclusion

PRRA-CapsNet is presented as an IoT-aware deep-learning approach for efficient predictive analytics in cloud computing. Using the Global Air Pollution Dataset, the model reports higher prediction accuracy, precision, recall and F1-score than TRANS_GRU and MSTVFFN, together with lower RMSE, MAE and prediction time.

- Accuracy improvement: about 4% over TRANS_GRU and 3% over MSTVFFN.
- Precision and recall improvement: about 3% and 2%.
- F1-score improvement: about 3% and 2%.
- RMSE reduction: about 54% and 42%.
- MAE reduction: about 53% and 41%.
- Prediction-time reduction: about 26% and 19%.

The study specifically evaluates air-pollution prediction in a cloud environment. Extensions to other domains or live IoT streams would require additional experimental validation.

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M.Nandhiya received her B.Sc Information Technology from NGM College, Pollachi. She had her Master of Computer Applications, from SVS Insitute ofTechnology under Anna University, Chennai. She holds her M.Phil degree in Computer Science at NGM College, Pollachi. She had 2 years 7 monthsexperience in the field of teaching. She is presently working as a Assistant professor in NGM College, Pollachi. Her research interest includes Data Mining, Big Data Analytics. Now she is pursuing her PhD degree at NGM College, Pollachi.



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