# CHAPTER 7

# OVERALL RESULTS AND DISCUSSION

The chapter analyses the performance of proposed methods and existing methods in terms of accuracy, precision, which are shown graphically to demonstrate the proposed works improvement.

## 7.1 AIR QUALITY DATA OF INDIA (2015-2020)

The comparison helps to understand the overall effectiveness of the proposed models with existing methods by evaluating with the dataset "Air Quality Data in India repository (2015 - 2020)" which is provided in to detect the air quality system using different performance metrics

### 7.1.1 Accuracy

The Comparison of accuracy of ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, WD-DTL is shown in Figure 7.1.

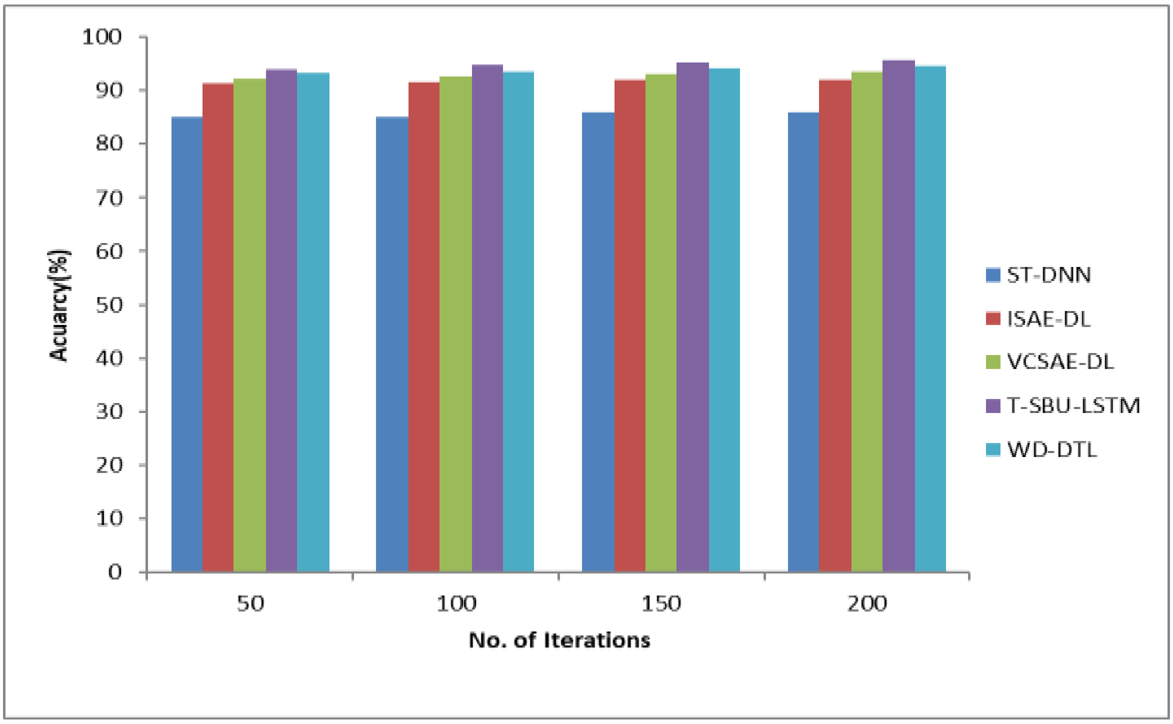

Figure 7.1 Evaluation of Accuracy

In Figure 7.1 shows the Comparison of accuracy in ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, and WD-DTL methods in all different iterations. The accuracy of ST-DNN is 93%, and the proposed methods, ISAE-DL is 98%, VCSAE-DL is 99.5%, T-SBU-LSTM is 99.4% and WD-DTL is 99.7.%.

### 7.1.2 Precision

Figure 7.2 presents the precision comparison of the models ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, and WD-DTL**.**

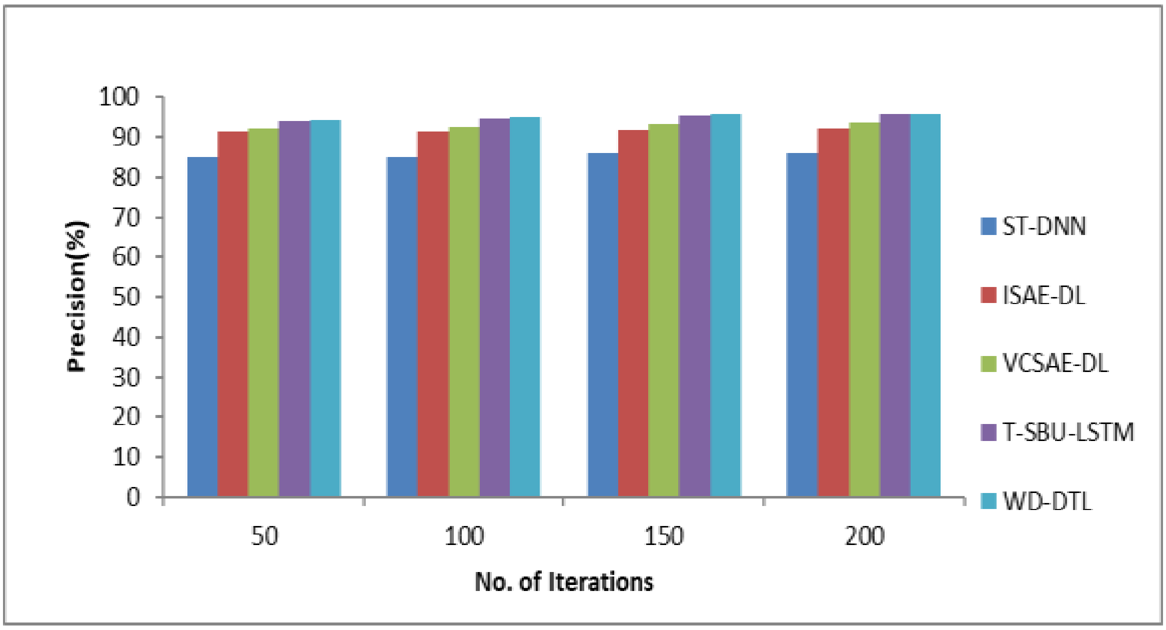

**Figure 7.2 Evaluation of Precision**

### 7.1.3 Sensitivity

Figure 7.3 displays the sensitivity values of various models ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, and WD-DTL across multiple iterations, illustrating how each model's architecture influences its effectiveness in identifying true positives.

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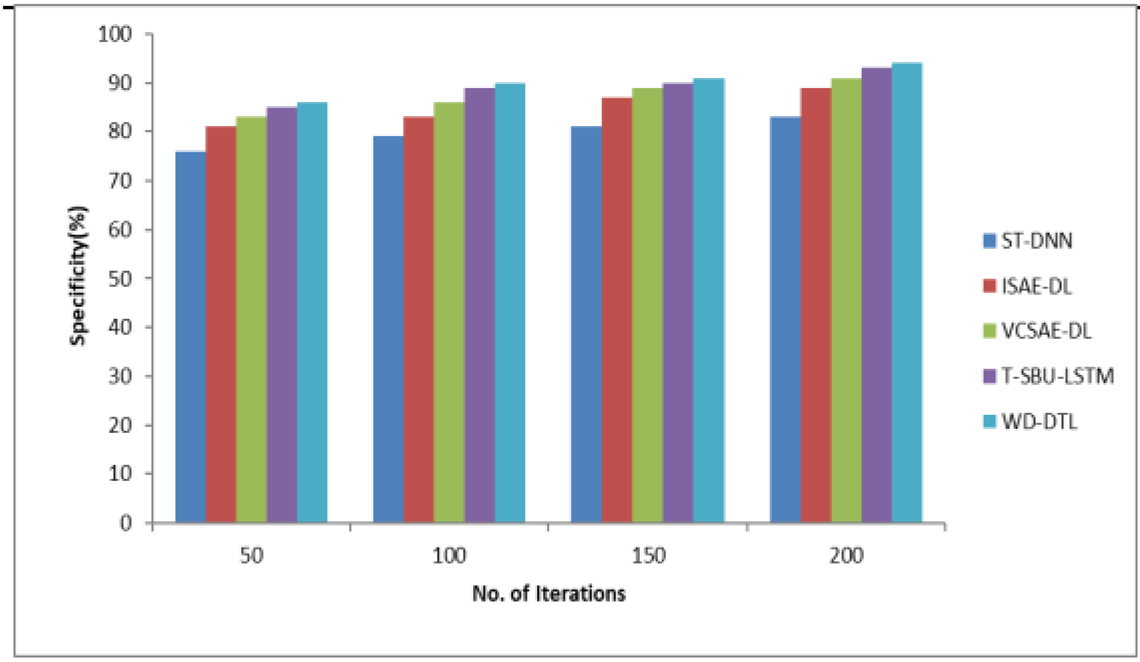

**Figure 7.3 Evaluation of Sensitivity**

### 7.1.4 Specificity

Figure 7.4 presents the specificity values of various models: ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, and WD-DTL across different iterations, highlighting each model's ability to accurately identify true negatives.

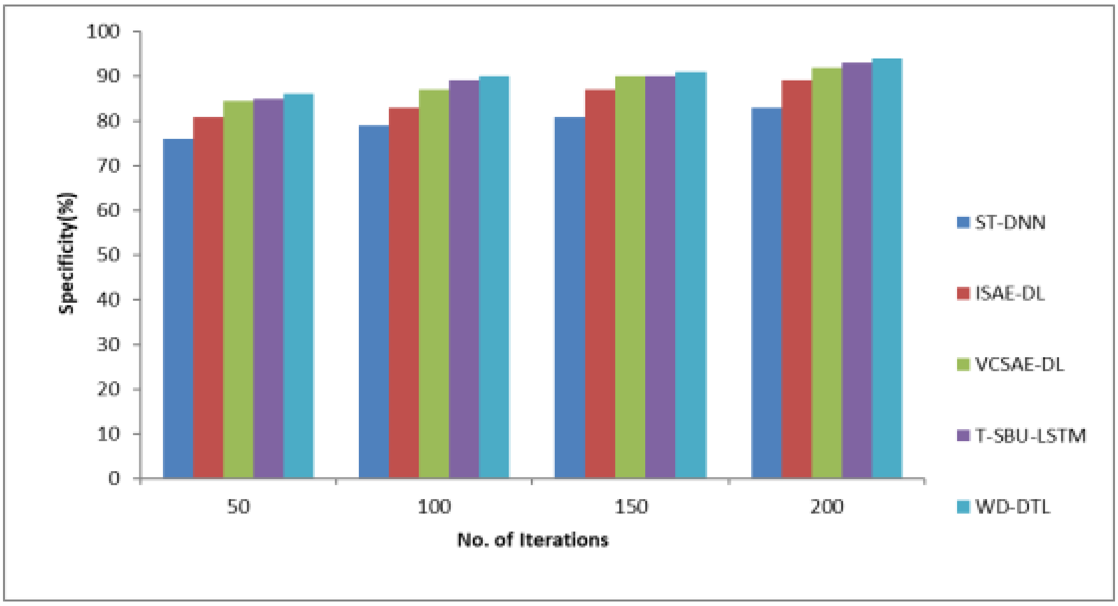

**Figure 7.4 Evaluation of Specificity**

### 7.1.5 Area under Curve (AUC)

Figure 7.5 shows the area under the curve (AUC) for different numbers of iterations for ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, and WD-DTL.

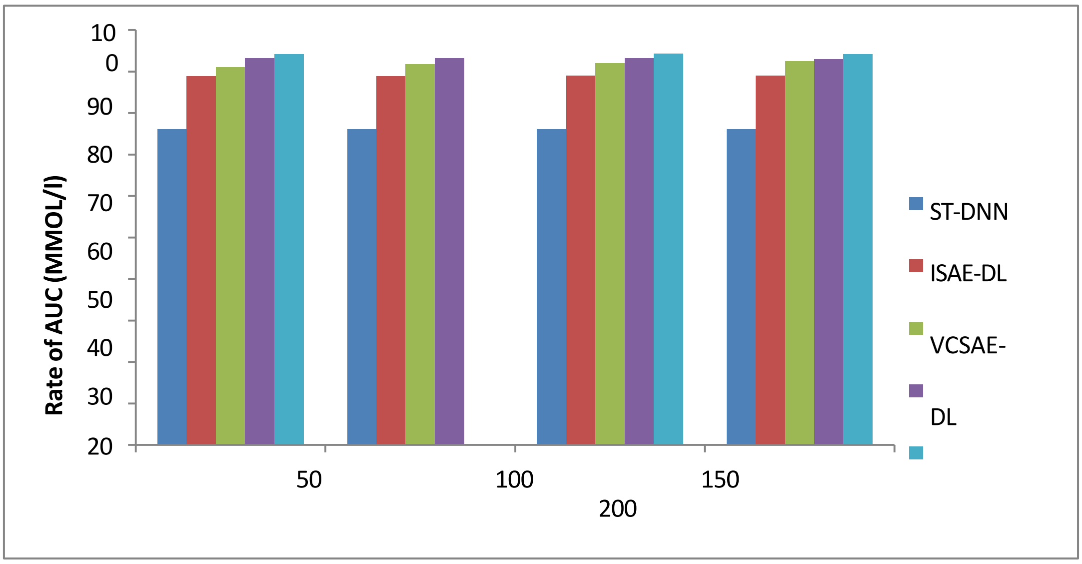

**Figure 7.5 Evaluation of AUC**

The AUC of ST-DNN is 76.1%, ISAE- DL is 88.97 %, VCSAE-DL is 92%, T-SBU-LSTM is 93 %, WD-DTL is 94.27 %, ST-DNN suggest low performance. Because the model struggles to differentiate between the positive and negative. ISAE-DL, VCSAE-DL,T- SBU-LSTM,WD-DTL indicates perfect discrimination, meaning the model perfectly distinguishes between positive and negative classes.

### 7.1.6 Matthew's Correlation Coefficient (MCC)

Figure 7.6 illustrates the Matthews Correlation Coefficient (MCC) for different iterations of the models: ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, and WD-DTL

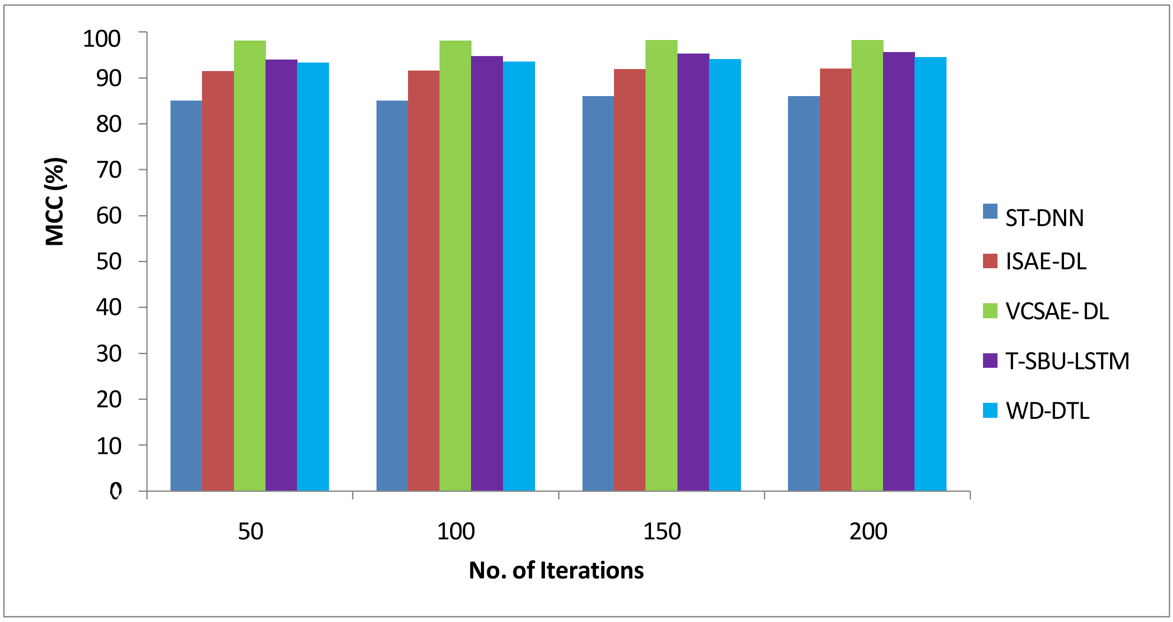

**Figure 7.6 Evaluation of MCC**

### 7.1.7 Mean Absolute Error Rate (MAER)

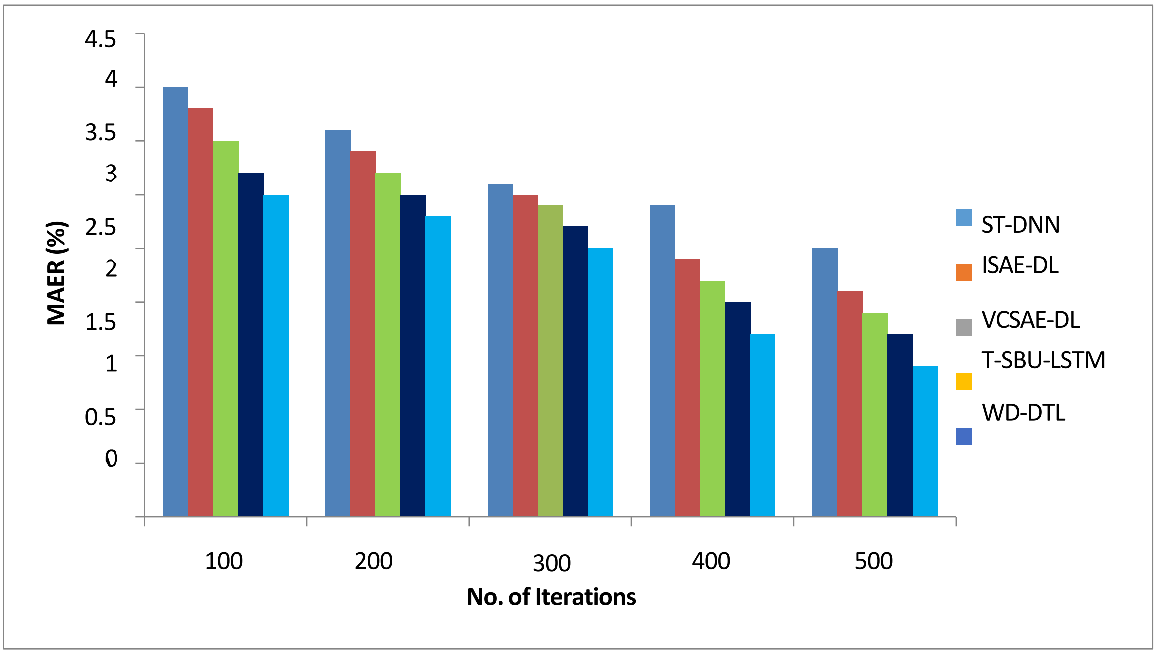

**Figure 7.7 Evaluation of MAER**

Figure 7.7 shows the comparison result of MAER of ST-DNN, ISAE-DL,VCSAE-DL, T-SBU-LSTM, and WD-DTL. The ST-DNN, ISAE-DL,VCSAE-DL,T-SBU-LSTM, WD-DTL is high error rate and WD-DTL is low error rate.

### 7.1.8 F-Measure

Figure 7.8 compares the F-Measure values of different models like ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM and WD-DTL.

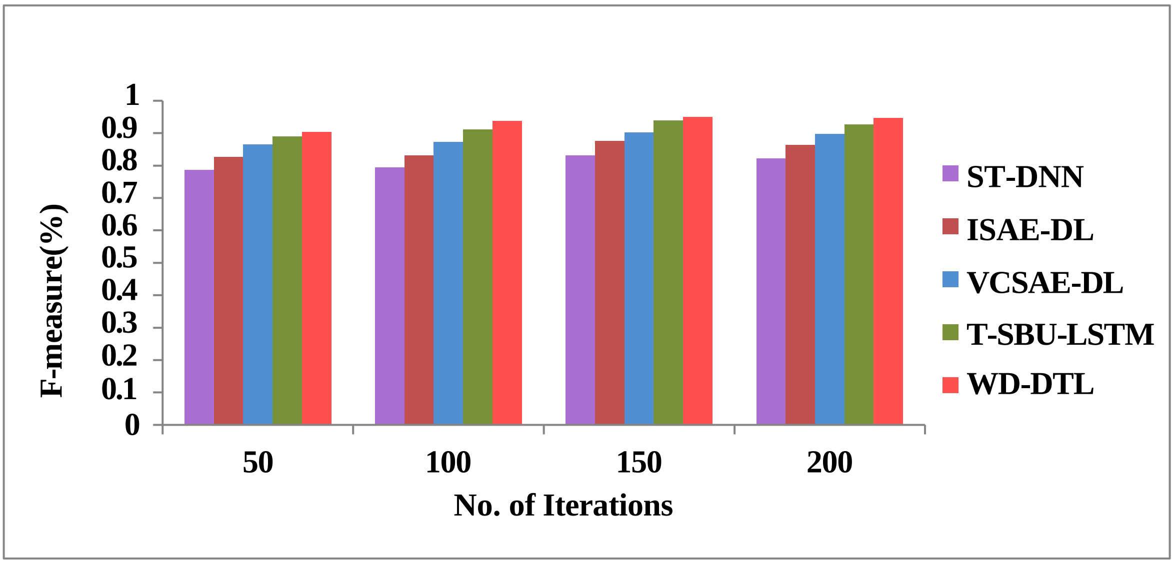

**Figure 7.8 Comparison of F-Measure**

The F-Measure of ST-DNN is 76.1%, ISAE- DL is 88.97 %, VCSAE-DL is 92%, T-SBU-LSTM is 93 %, WD-DTL is 94.27 %, ST-DNN suggest low performance. Because the model struggles to differentiate between the positive and negative. ISAE-DL, VCSAE-DL,T- SBU-LSTM,WD-DTL is 15.21%, 9.61%, 5.46% and 2.16% indicates perfect discrimination, meaning the model perfectly distinguishes between positive and negative classes.

The ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, and WD-DTL models, exhibit varying levels of performance across different metrics. ST-DNN as a baseline model demonstrates the limitations of simpler architectures in capturing complex data patterns and in detecting true positives. The use of stacked autoencoders enables the ISAE-DL model leading to improved performance over the baseline model highlights the benefits of deep learning techniques in capturing complex patterns.

The ability of VCSAE-DL model to handle uncertainty and variability in data can be beneficial for air quality prediction, as environmental factors can be highly variable.

T-SBU-LSTM model leverages the power of LSTM networks to capture temporal dependencies, with its strong performance in handling sequential data, is particularly well-suited for air quality prediction, as air quality is influenced by various factors that change over time. WD-DTL consistently outperforms other models, highlighting the effectiveness of domain adaptation and transfer learning techniques. By leveraging knowledge from related domains, this model generalizes well to new, unseen data, especially in scenarios with limited training data. This finding suggests that incorporating domain adaptation strategies can significantly enhance the performance of deep learning models. By considering these factors and leveraging the insights from the analyzed models, combining the domain adaptation capabilities of WD-DTL with the temporal modeling capabilities of T-SBU-LSTM, can lead to even more accurate and reliable air quality prediction models, contributing to better air quality management and public health.

## 7.2. VALIDATION OF ALGORITHMS

The Performance of the proposed methods, ISAE-DL, VCSAE-DL, T-SBU- LSTM and WD-DTL are validated using the air quality dataset which range between the years 2010 to 2023 which is obtained from the Kaggle repository. (https://www.kaggle.com/datasets/abhisheksjha/time-series-air-quality-data-of-india) The dataset contains 100564 instances and 15 attributes. The data from the Central Control Room for Air Quality Management provides valuable insights into air quality trends in Indian cities over 13 years. It aids researchers, policymakers, and the public in identifying pollution areas, assessing control measures, and developing strategies for improving public health. This dataset constitutes 453 Indian cities, in this study southern Indian station. Totally 100564 data samples are collected from the cities which is divided into training (60%) and testing (40%) for experimental analysis.

### 7.2.1 Accuracy

Figure 7.8 compares the performance of proposed methods ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM and WD-DTL for different iterations on the air quality dataset which range between the years 2010 to 2023. When comparing the accuracy of various air quality prediction methods after 200 iterations, WD-DTL has been found to be superior to ST-DNN, ISAE-DL, T-SBU-LSTM, and WD-DTL by margins of 10.17%, 7.42%, 3.81% and 1.72% respectively.

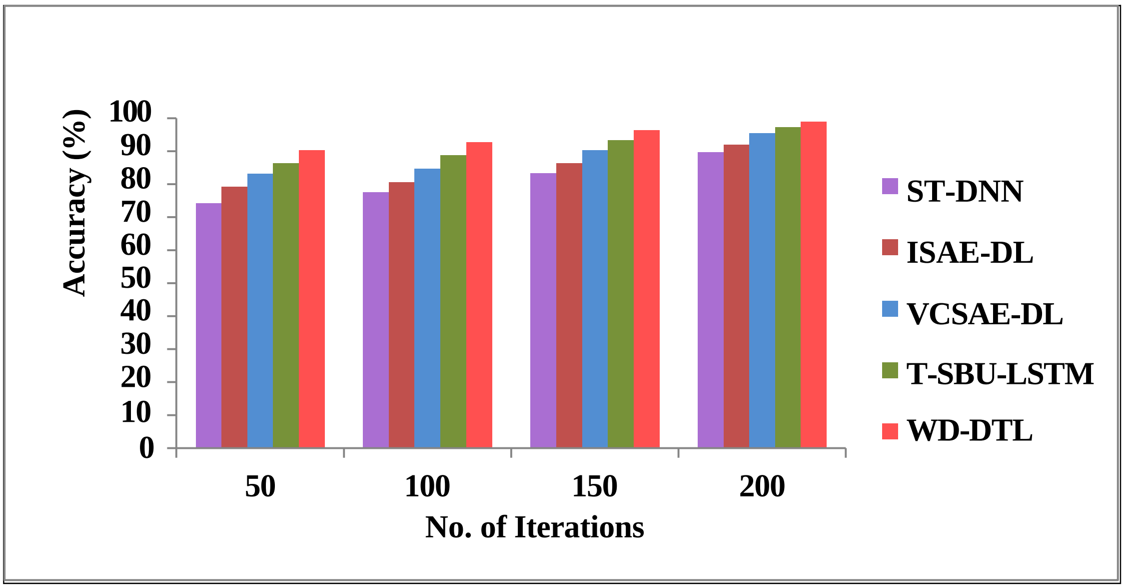

**Figure 7.9 Evaluation of Accuracy**

### 7.2.2 Precision

Figure 7.9 shows accuracy of ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, and WD-DTL algorithms across a range of iterations. The accuracy of the WD-DTL standard is maximized with an iteration count of 200 is 11.45%, 7.78%, 4.34% and 2.15% than ST-DNN, ISAE-DL, VCSAE-DL and T-SBU-LSTM, WD-DTL for air quality prediction.

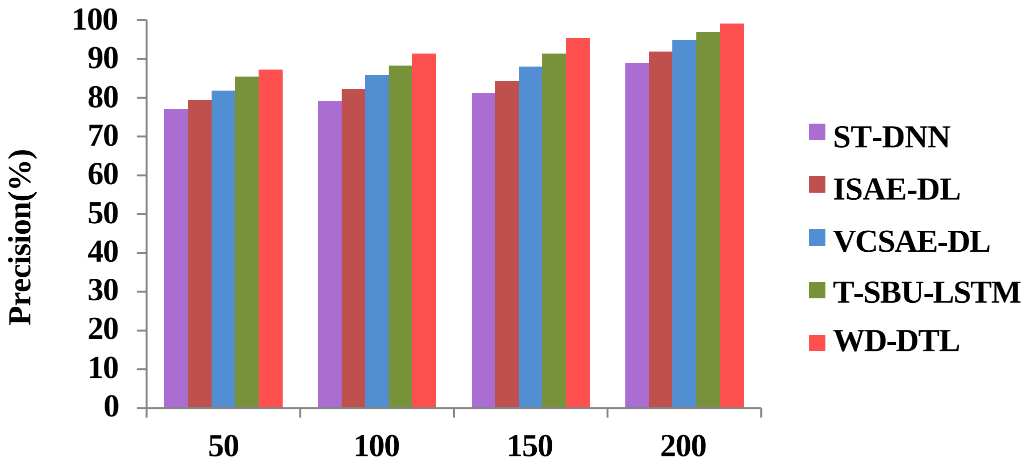

**Figure 7.10 Evaluation of precision**

### 7.2.3 Sensitivity

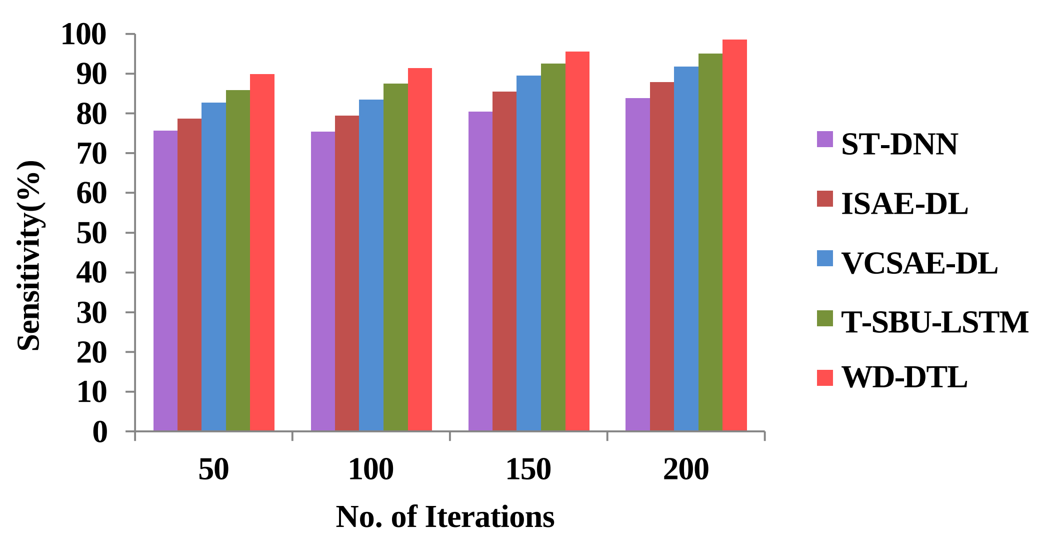

**Figure 7.11 Evaluation of Sensitivity**

Figure 7.3 displays the sensitivity values of various models ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, and WD-DTL across multiple iterations, illustrating how each model's architecture influences its effectiveness in identifying true positives. ST-DNN, with a sensitivity of 82%, demonstrates limitations in true positive detection, likely due to its simpler design, which may result in higher false negatives. ISAE-DL improves upon this with a sensitivity of 91.5%, using stacked autoencoders to capture richer features and enhance detection capability. VCSAE-DL and T-SBU-LSTM, both achieving 90% sensitivity, show further advancements; VCSAE-DL's variational component aids in managing data uncertainty, while T-SBU-LSTM's LSTM elements better handle sequential data. WD-DTL, with the highest sensitivity at 97%, benefits from domain adaptation or transfer learning, allowing it to generalize effectively across diverse data sources and maintain high true positive accuracy.

### 7.2.4 Specificity

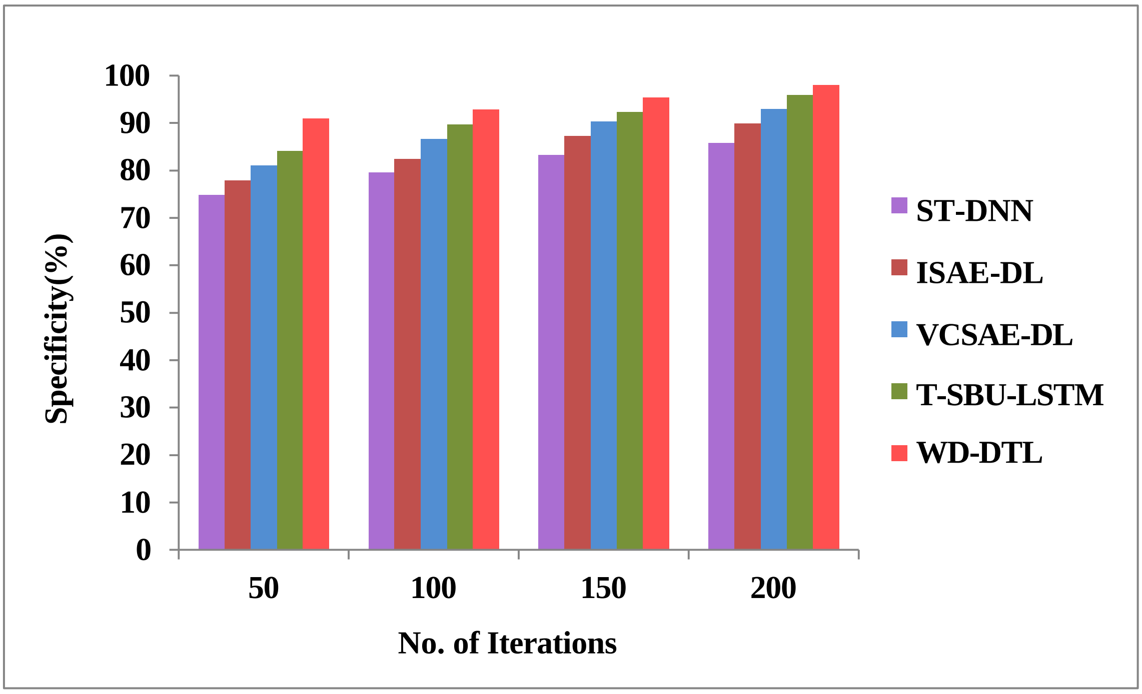

**Figure 7.12 Evaluation of Specificity**

Figure 7.4 presents the specificity values of various models: ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, and WD-DTL across different iterations, highlighting each model's ability to accurately identify true negatives. With a specificity of 83%, ST-DNN demonstrates a relatively basic level of negative detection, likely due to its simpler architecture, which may not adequately capture the subtleties required to minimize false positives. ISAE-DL shows an improvement, achieving 89% specificity, indicating that its stacked autoencoders are more effective at differentiating between relevant and irrelevant features, thereby enhancing true negative identification. VCSAE-DL and T-SBU-LSTM further increase specificity to 92% and 93%, respectively, with VCSAE-DL utilizing variational inference to manage data variability, while T-SBU-LSTM's LSTM components improve detection accuracy in sequential data. WD-DTL achieves the highest specificity at 94%, suggesting that its domain adaptation or transfer learning capabilities enable it to generalize effectively across diverse datasets, making it particularly adapt at minimizing false positives in various contexts.

### 7.2.5 Area under Curve (AUC)

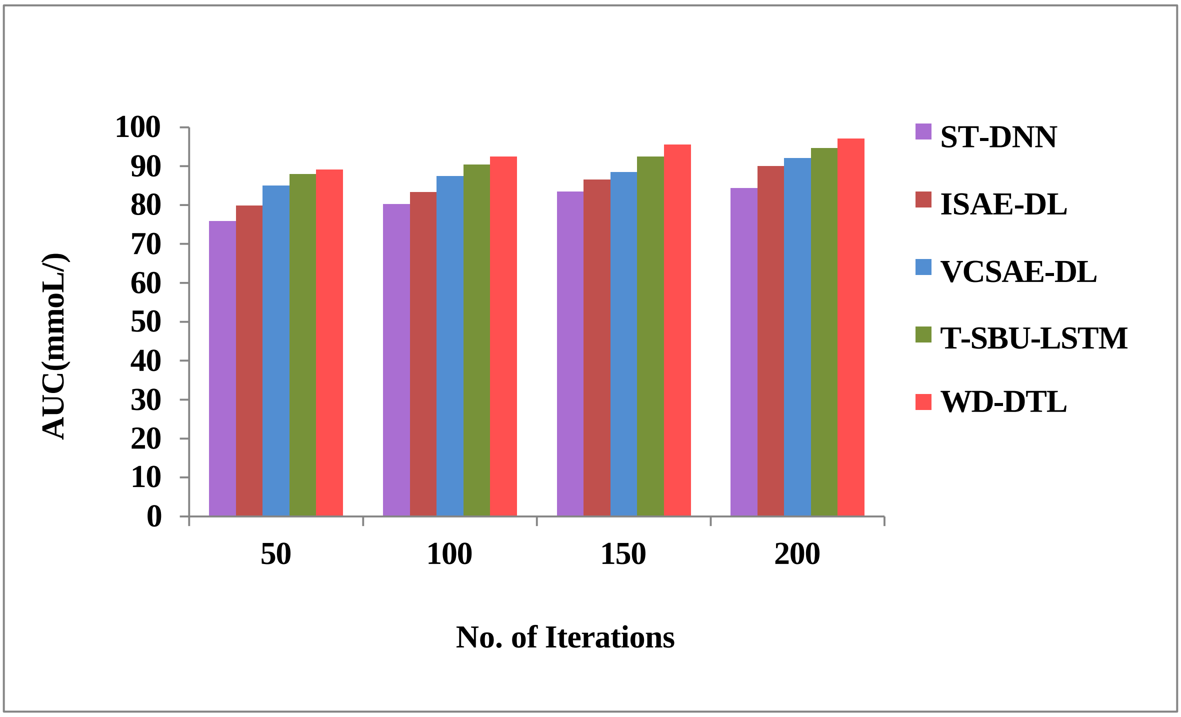

Figure 7.13 Evaluation of AUC

Figure 7.13 shows the area under the curve (AUC) for different numbers of iterations for ST-DNN, ISAE-DL, VCSAE-DL,T-SBU-LSTM,WD-DTL.The AUC of ST-DNN, ISAE- DL, VCSAE-DL,T-SBU-LSTM,WD-DTL by margins of 15.08%, 7.9%,5.48% and 2.62% respectively. ST-DNN suggest low performance. Because the model struggles to differentiate between the positive and negative. ISAE-DL, VCSAE-DL,T-SBU- LSTM,WD-DTL indicates perfect discrimination, meaning the model perfectly distinguishes between positive and negative classes.

### 7.2.6 Matthew's Correlation Coefficient (MCC)

Figure 7.14 illustrates the Matthews Correlation Coefficient (MCC) for different iterations of the models: ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, and WD-DTL. ST-DNN achieves an MCC of 79.1%, indicating a moderate level of classification performance. In contrast, ISAE-DL shows a notable improvement with an MCC of 94.14%, reflecting its enhanced ability to effectively balance true positives, true negatives, false positives, and false negatives. VCSAE-DL and T-SBU-LSTM further excel with MCCs of 98.2% and 98.5%, respectively, demonstrating their strong capacity for accurate classification with minimal errors. WD-DTL achieves the highest MCC at 99.62%, showcasing outstanding performance and a remarkable ability to classify instances correctly while reducing misclassifications. Overall, the MCC trends highlight the superior performance of more advanced models in delivering accurate and reliable classifications across iterations.

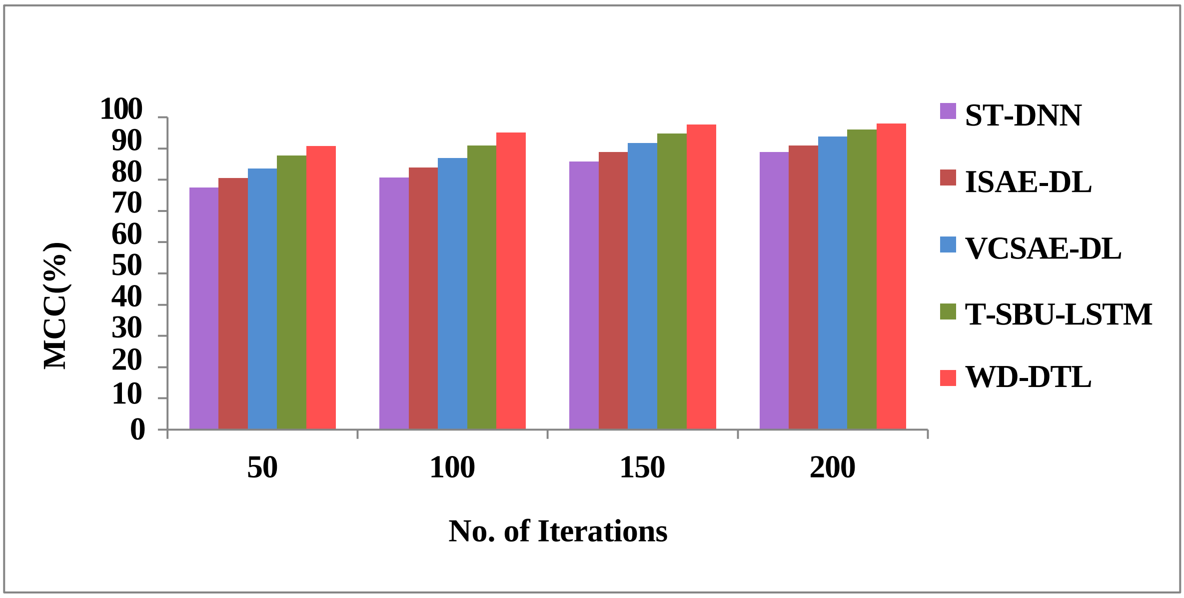

**Figure 7.14 Evaluation of MCC**

### 7.2.7 Mean Absolute Error Rate (MAER)

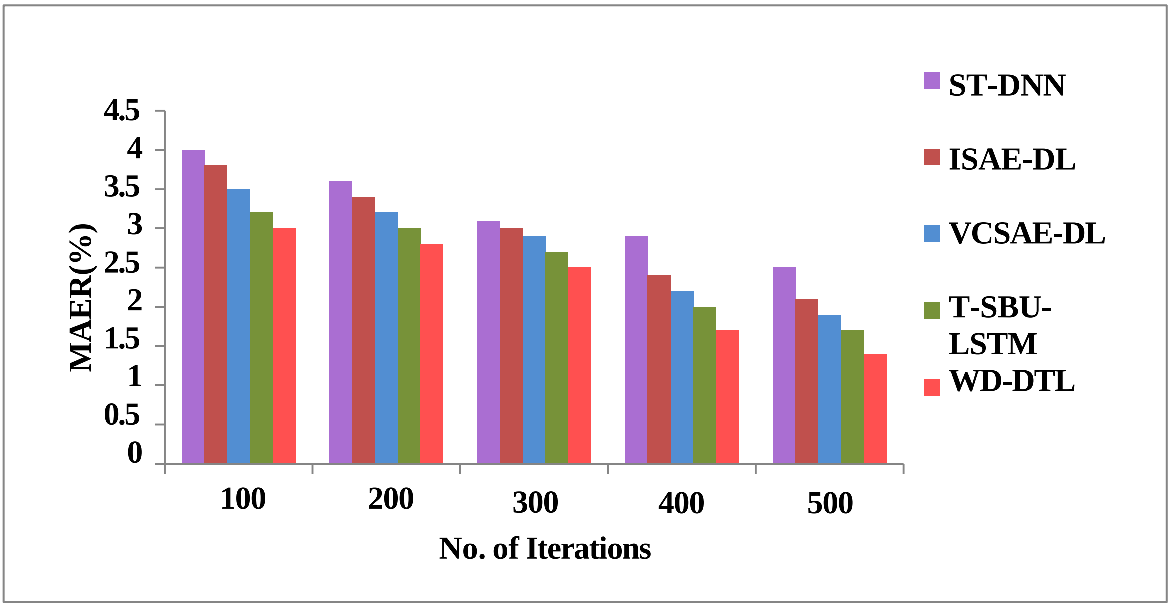

**Figure 7.15 Evaluation of MAER**

Various error rates for several models are shown in Figure 7.15. These models include ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM and WD-DTL. When compared to ISAE-DL, ST-DNN, VCSAE-DL, T-SBU-LSTM, and WD-DTL models, respectively, with 500 training epochs, the error rate of WD-DTL is found to be 47.82%, 40%, 29.41%, and 14.28% lower.

### 7.2.8 F-Measure

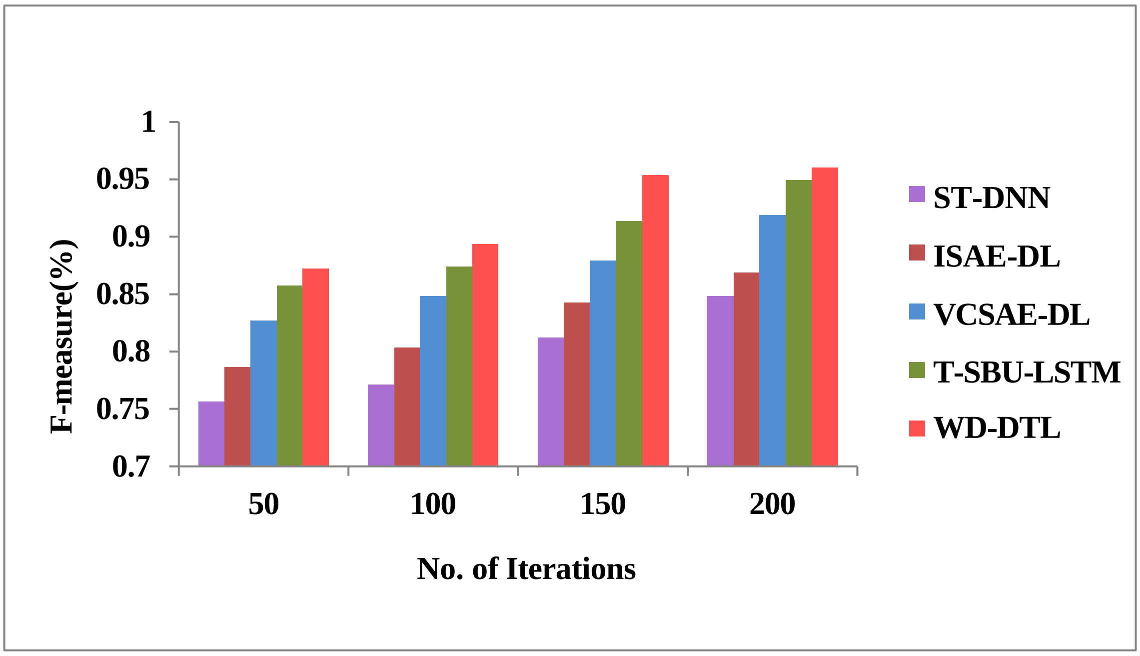

**Figure 7.16 Evaluation of F-measure**

Figure 7.16 shows the F-measures for different numbers of iterations for ST-DNN, ISAE-DL, VCSAE-DL, T-SBU-LSTM, WD-DTL. The ST-DNN is 15.08%, ISAE- DL is 7.9%, VCSAE-DL is 5.48%, T-SBU-LSTM is 2.62% respectively. ST-DNN suggest low performance. Because the model struggles to differentiate between the positive and negative. ISAE-DL, VCSAE-DL, T-SBU-LSTM,WD-DTL indicates perfect discrimination, meaning the model perfectly distinguishes between positive and negative classes.