CHAPTER 8

CONCLUSION AND FUTURE ENHANCEMENT

8.1 CONCLUSION

Recently, concerns about air quality have grown among the public due to environmental problems caused by excessive air emissions. Negative effects of global warming and ozone depletion include rising sea levels, accelerated glacier melting, temperature variations, and climate shifts in the Arctic and Antarctic. Since the industrial revolution, air pollution has risen significantly. The transition from rural to urban population is often seen as a major factor in raising the pollution level. Air quality prediction is concerned with the prediction of the air quality in a certain area. Predictions of local air quality have been attempted using a number of different approaches. The Machine learning systems do not yield are liable result for making long-term forecasts of air quality. Thus, this study presented a variety of deep learning techniques in developing a more accurate air quality predicate system.

The first work of research contribution is an Improved Sparse Auto Encoder using Deep Learning (ISAE-DL) model was developed using a sparse autoencoder method. The particulate matter and meteorological data, a combined approach of Spatial and temporal network was utilized. Furthermore, neural network layer were employed to gather relative information. A prediction model was generated by training data.

The Second work of research contribution is an Voronoi Clustering Sparse Auto Encoder-Deep Learning (VCSAE-DL) model was used to address long term dependencies for improved air quality system. In this method, places with a high degree of temporal and spatial correlation were clustered using the Manhattan distance metric. To ensure that all data were considered, the clustering process was halted, and the construction of clusters continued using other centers.

The Third work of research contribution is the Transferred Stacked Bi-directional and Uni-directional Long Short-Term Memory (T-SBU-LSTM) model was proposed to address the learning issues associated with long-term dependencies in LSTM for the air quality prediction model.

The addition of an LSTM module to the proposed T-SBU-LSTM improved first-hour forecasts, while the inclusion of a CNN module proved more beneficial for longer-term forecasts due to CNN's capacity is used to gather and excerpt the information from spatial and Temporal data.

The last work of Research contribution is the Wasserstein Distance-Deep Transfer Learning (WD-DTL) model was utilized to reduce the learning time of Transfer Learning. The source and Target domain is used to learn air quality features in a deep transfer learning methods. Finally, the developed strategies were evaluated to handle locations with long-time delays for better air quality prediction. Based on the final results, the results of WD-DTL model demonstrate that the suggested provides higher accuracy results of 99.903%, while other approaches like ISAE-DL, VCSAE-DL, T-SBU-LSTM, WD-DTL yields accuracy of 96 %, 95%, 98.5% and 97% respectively.

The Wasserstein distance-based deep transfer learning model for air quality prediction holds substantial societal benefits for public health, policy, and the environment. The model's ability to adapt across diverse data distributions, using transfer learning techniques combined with the Wasserstein distance, has the potential to improve the accuracy and reliability of air quality prediction, which can influence several key societal aspects. By delivering accurate, real-time air quality forecasts across various regions, the model can provide early warnings for areas with elevated pollution levels. The incorporation of Wasserstein distance into transfer learning enhances the model's ability to perform effectively across regions with diverse pollution patterns and environmental conditions. This is especially valuable in areas where air quality can vary significantly between cities or even within different parts of a single city. By improving the model's adaptability to local factors, it ensures more precise and context-specific predictions, enabling better-informed decision-making at both individual and community levels.

Moreover, the model can support long-term environmental planning by providing insights into pollution trends and their impact on ecosystems, enabling cities to create green spaces or implement other initiatives to mitigate pollution. The model can enhance public health, equip communities with actionable air quality data, and support the development of sustainable policies to reduce pollution.

8.2 FUTURE WORK

The study can be extended to include satellite imagery, enabling the development of predictive models for individual areas within a city. Additionally, improving model predictions by reducing the feature space and identifying an optimal feature selection method can enhance the results. Implementing the model on an efficient hardware platform, such as GPUs or edge computing devices, can further optimize its performance for real-time applications. Future research could focus on predicting AQI levels in India post-COVID-19, incorporating additional factors influencing air pollution and exploring its association with related diseases. As future work, the Hybrid deep learning methods can focus on predicting AQI after COVID 19 in India with the involvement of additional factors after air pollution, further associating diseases through air pollution will be focused on future.