domain knowledge. It also provides dimensionality reduction and is robust against overfitting characteristics. The experimental results show the feasibility of our generic model, which will increase the safety of passengers as well as serve the public interest. We have tested the robustness of our model in the case of a large dataset, which proves the efficacy of our model.

References

[1] U. Desa, World urbanization prospects, the 2011 revision, Population Division, Department of Economic and Social Affairs, United Nations Secretariat, 2014.

[2] G. Niu, S. Lee, B. Yang and S. Lee, Decision fusion system for fault diagnosis of elevator traction machine, Journal of Mechanical Science and Technology, 22, pp. 85–95, 2008.

[3] R. Zhang, Z. Peng, L. Wu, B. Yao and Y. Guan, Fault diagnosis from raw sensor data using deep neural networks considering temporal coherence, Sensors, vol. 17, (3), pp. 549, 2017.

[4] M. Xia, T. Li, L. Xu, L. Liu and C.W. de Silva, Fault diagnosis for rotating machinery using multiple sensors and convolutional neural networks, IEEE/ASME Transactions on Mechatronics, vol. 23, (1), pp. 101-110, 2018.

[5] F. Calimeri, A. Marzullo, C. Stamile, and G. Terracina, Graph based neural networks for automatic classification of multiple sclerosis clinical courses, in Proceedings of the ESANN 2018.

[6] I. Fernández-Varela, D. Athanasakis, S. Parsons, E. Hernández-Pereira, and V. Moret-Bonillo, Sleep staging with deep learning: A convolutional model, in Proceedings of the ESANN 2018.

[7] J. Hänninen and T. Kärkkäinen, Comparison of four-and six-layered configurations for deep network pretraining, in Proceedings of the ESANN 2016.

[8] R. Huet, N. Courty and S. Lefèvre, A new penalisation term for image retrieval in clique neural networks, in Proceedings of the ESANN 2016.

[9] F. Fogelman-Soulie, Y. Robert and M. Tchuente, Automata Networks in Computer Science: Theory and Applications. Manchester University Press and Princeton University Press, 1987.

[10] P. Madani and N. Vlajic, Robustness of deep autoencoder in intrusion detection under adversarial contamination, in Proceedings of the 5th Annual Symposium and Bootcamp on Hot Topics in the Science of Security, 2018, pp. 1..

[11] S. Timotheatos, G. Tsagkatakis, P. Tsakalides, and P. Trahanias, Feature extraction and learning for RSSI based indoor device localization, in Proceedings of the ESANN 2017.

[12] G. Jiang, P. Xie, H. He, and J. Yan, Wind turbine fault detection using a denoising autoencoder with temporal information, IEEE/ASME Trans. Mechatronics, vol. 23, no. 1, pp. 89–100, 2018.

[13] N. Japkowicz, S. J. Hanson and M. A. Gluck, Nonlinear autoassociation is not equivalent to PCA, Neural Comput., vol. 12, (3), pp. 531-545, 2000.

[14] L. Breiman, Random forests, Machine Learning, vol. 45, no. 1, pages 5-32. 2001.

[15] A. Liaw and M. Wiener, Classification and regression by random forest, R News, vol. 2, (3), pp. 18-22, 2002.

[16] T. Huynh, Y. Gao, J. Kang, L. Wang, P. Zhang, J. Lian and D. Shen, Senior Member, IEEE, and Alzheimer's Disease Neuroimaging Initiative, Estimating CT image from MRI data using structured random forest and auto-context model, IEEE Transactions on Medical Imaging, vol. 35, (1), pp. 174-183, 2016.

[17] Z. Liu, Member, IEEE, B. Tang, X. He, Q. Qiu, and F. Liu, Class-specific random forest with cross-correlation constraints for spectral–spatial hyperspectral image classification, IEEE Geoscience and Remote Sensing Letters, vol. 14, (2), pp. 257-261, 2017.