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LIFE TIME PREDICTION OF AN ELECTROMAGNET RELAY USING CLUSTERING BASED PRINCIPAL COMPONENT ANALYSIS WITH HYBRID DEEP LEARNING MODEL

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ABSTRACT
The estimation of the electromagnet relay remaining useful life is highly crucial to maintain reliability and avoid unscheduled breakdowns in various applications. The objective of this research work will be to design a model with much higher precision and efficiency utilizing PCA coupled with a hybrid deep learning architecture of Bi-LSTM along with Bi-GRU. The C-MAPSS dataset was of reduced dimensionality, since PCA has been applied to eliminate data redundancy while retaining crucial characteristics, and then K-means clustering is applied to classify the data; afterwards, the Bi-LSTM and Bi-GRU models are implemented for RUL relay prediction. The proposed method in comparison with typical deep learning models has a Mean Absolute Error of 0.021 and an R² of 0.996. Results developed reflect how the model can produce some very powerful prediction, however; what it really shows is great potential for this approach with respect to predictive maintenance of electromagnet relays. PCA may well amalgamate with Bi-LSTM and Bi-GRU models to achieve great scalability according to the maintenance engineering, which offers practical applications in improving the lifetime of the electromagnet relays.
Keywords: *Electromagnet Relay, Remaining Useful Life, Bidirectional Long Short Memory with Bidirectional Gated Recurrent Unit, Principal Component Analysis, K Means Clustering.*

1. Introduction

The Electromagnetic Relay (EMR) is a complex part and is used for different electrical systems, and it includes critical safety applications and consumer products in industries such as aviation and nuclear power. Extensive studies have focused on the failure modes and mechanisms of EMR, particularly electrical contact degradation, to enhance process and material components (Yuming et al., 2023). Automation has contributed significantly to advancements in the manufacturing and reliability of Electromagnetic Relays. Methods with respect to population have been demonstrated to be a cost-effective solution for assessing the reliability of mass produced EMR. Commonly, incorporating EMRs into a condition monitoring program in operation and preservation budgets have been cost-prohibitive for different fields (Verstraete et al., 2017). Even so, advent of digital industrialization, there is now extraordinary to vast amounts of network and element monitoring data (Roman et al., 2017).

Organizations focusing on enhancing the reliability of their assets have been investing in Prognostics and Health Management (PHM) systems to boost availability and reliability while reducing maintenance costs (Liu et al. 2024). A few studies have focused on leveraging data collected from Internet of Things assets and sensors to predict maintenance events, including fault prognostics, detection and diagnostics. In the PHM literature, different approaches, including statistical, machine learning (ML) methods and physics based, have been demonstrated to tackle the remaining useful life (RUL) prediction problem. Physics based methods involve creating mathematical modelling that represent the degrading model of failure mechanisms. These approaches necessitate prior understanding of degrading and provides precise RUL prediction when the failure can be characterized using its physical properties (Hu et al., 2023). In traditional ML, models require a sufficient amount of labelled historical data to achieve a high level of performance (Ding & He, 2017). Which need to deal with that collaborator with already implemented time-based maintenance on the benefits, which constructing the observation of run to failure behaviours very less than usual (Winkel et al., 2023). To deploy the challenges, practitioners and researchers must construct methods to manage censored data or create additional data, resulting in imperfect models that may not exactly detect the real-world scenarios (Liu et al., 2018). While sufficient run to failure data is available, algorithms utilized on a specific dataset usually can't be generalized to various datasets (Sateesh Babu et al., 2016).

Prognostics and Engineering maintenance and are vital in various industries, including manufacturing, aerospace, heavy industry and automotive (Roman et al., 2021a). Conservative strategies like scheduled preventive maintenance and breakdown corrective maintenance are increasingly insufficient to meet the growing demands for reliability and efficiency (Zhang et al., 2020). Particularly, Smart PHM technologies, which are also known as condition-based maintenance, and are exhibiting the remarkable industrial applications (Wang et al., 2020). However, deep learning (DL) networks have come out as highly effective structures for various applications, giving significant ability to increase the performance in better prognostics. DL is respected by its deep network model, which involves stacking multi-layers to comprehensively capture representation information from raw input data (Zheng et al., 2016). Complex DL model captures high level data, enabling more efficient extraction of features when compared to ML networks (Qin et al., 2022). Given the high dimensionality of raw data from machinery health monitoring, and data in image processing research, DL architectures hold substantial promise for applications in PHM and RUL estimation. As EMR is an electrical actuator used widely in automation purposes the maintenance problem should not be there in automation field which may arise due to EMR, so the testing report may be sent by the production company but not actual life time. They may promise some life time for EMR but not achieved in practical. With the help of AI, we can predict the lifetime with the ample of data available the main objective of this paper is to product the failure free relay and the practically possible final lifetime of the the relays using the AI (Zeiler, 2014).

Robots are capable of learning to modify their performance in unexpected and changing circumstances (Robu et al., 2018). Internet of Things, machine learning, and the foundations of electronic health management and prognostics (Gan, 2020). Sliding window characteristics are used to construct models in both the more contemporary Convolutional Neural Network (CNN) method and more conventional regression-based approaches (Zheng et al., 2017). In recent years, prognostic performance evaluation has attracted a lot of interest. Concepts related to prognostics are currently poorly defined and subject to variable and unclear interpretations (Saxena et al., 2010). To handle the information management and prediction demands for meeting these goals, the field of prognostics and health management (PHM) is being formalised (Pecht, Mathew & Gullo, 2017). During the manufacture procedure, anode-to-cathode transfer created noticeable pips and craters that could result in premature relay failures (Leung & Lee, 1991). Printed Circuit Board (PCB) designs are frequently neglected by circuit designers (Khater, 2020). However, thorough and meticulous PCB design methods are closely linked to both the performance of the circuits and the calibre of the measurements (Ghahramani et al., 2020). These design methods can be used for almost any type of circuit, including digital, analogue, radio frequency, and power applications (Yin & Liu, 2020). A basic overview of the typical issues encountered while building high-performance and high-speed PCBs is given in this study (Yin & Huang, 2022). Although the fundamentals of PCBs are not covered in this tutorial paper, it does offer practical and widely used techniques for producing expert layouts (An et al., 2020). For circuits operating at up to 30 GHz, this entails researching bypass capacitors, different PCB architectures that provide strong signal integrity, and on-board transmission lines and their matching strategies (Motahari-Nezhad & Jafari, 2023). The term "smart manufacturing" describes optimization strategies applied to production processes through the use of sophisticated analytics techniques (Lei et al., 2018). There is a growing demand for efficient and effective data management strategies due to the extensive use of industrial internet of things (IIOT) sensors in manufacturing operations (Deutsch & He, 2017). Using artificial intelligence and machine learning to leverage production data can result in intelligent and effective automation (Kirschbaum et al., 2020).

2. Related Works

(Sun et al., 2018), presented railway safety relay prediction using principal component analysis (PCA), fisher discrimination and back propagation network (BPN). Initially, the dimensionality was reduced by the PCA and fisher discrimination was used to validate the degradation parameter variation. Finally, the BPN was used for the prediction process and the accuracy value attained was 88.9%. (Li et al., 2021), developed EMR prediction approach using the long short term memory neural network (LSTM) with harris hawk algorithm (HHA). Initially, the signals were decomposed by empirical mode decomposition (EMD) and various sub elements and residual elements were captured. Then, the prediction process was performed by the LSTM, group handling model and HHA.

(Li et al., 2018), designed an EMR prediction model using a convolutional neural network (CNN). To assist the CNN model is better feature extraction, the time windowing model was presented. The normalized data was utilized as input and C-MAPSS dataset was considered. The RMSE performance was analyzed by varying the number of layers and window size in CNN.

(Kirschbaum et al., 2022), developed prognostics for EMR using Temporal Convolutional Network (TCN). The features were obtained from raw and large volume data and Monte carlo dropout was used for estimating uncertainty. Then, the TCN was used for analyzing long series of multivariate data. Finally, the performance was analyzed by sub-sample model, and then the RMSE and MAE values achieved were 287.2 and 242 respectively. (Zhao et al., 2017), presented a prediction of RUL for EMR using particle filter-based models. There were three characteristic features like less data parameter measurement, incompletion of run to failure data and no approach available for physical degrade model. Then, three major stages like estimating parameters, validation and prediction of RUL. Data from 9 relays were utilized to define the values of the initial parameter distribution.

(Roman et al., 2021b), Only lately have electrochemical capacitors (ECs) been explored as a potential substitute power source for the telemetry sensors of drilling equipment used in oil and gas or geothermal exploration. Compared to other storage devices, such as Li-ion batteries, the lifespan analysis and modelling of ECs are not as well documented in the literature. Over the past ten years, deep learning applications have flourished in a variety of fields, such as computer vision and natural language comprehension (Fink et al., 2020). The availability of large amounts of data, algorithmic discoveries, and hardware developments have all contributed to the dynamic growth of deep learning. The use of deep learning techniques for identifying, diagnosing, and forecasting defects in complex industrial assets has been restricted, despite the fact that these assets have been widely monitored and that a significant volume of condition monitoring signals has been gathered. The current study offers a comprehensive assessment of the latest advancements, motivators, difficulties, prospective fixes, and research requirements in the area of deep learning applied to applications in prognostics and health management (PHM).

(Zheng et al., 2014), Due to its wide range of applications in several fields, including bioinformatics and health informatics, time series classification—especially multivariate classification—has received a lot of attention in the literature. As a result, numerous algorithms have been created for this task. The state-of-the-art performance is attained by combining closest neighbour classification (especially 1-NNg) with dynamic time warping (DTW). However, the time consumption of 1-NN with DTW increases linearly with the size of the data set. Traditional feature-based classification techniques are typically more efficient but less effective than 1-NN with DTW since their effectiveness typically depends on the calibre of hand-crafted features. (Yang et al., 2015), Extracting useful information for activity identification is a crucial yet difficult challenge in this problem. The majority of current work uses shallow feature learning architectures and heuristic hand-crafted feature design, which are unable to identify the distinctive characteristics needed to correctly classify various activities.

We suggest a methodical feature learning approach for the HAR problem in this research. In order to automate feature learning from the raw inputs in a methodical manner, this approach uses deep convolutional neural networks (CNN). The learnt features are regarded as the higher-level abstract representation of low-level raw time series signals through the use of the deep architecture.

3. Proposed Methodology

The aim of PHM is to enhance the operational availability, boost system reliability, and minimize maintenance costs and safety through continuous monitoring of facility conditions. Estimating the RUL based on historical data is crucial to optimize maintenance schedules to prevent engineering failures and minimize associated costs. This technique introduces a PCA for dimensionality reduction, KMC for identifying patterns and Bi-LSTM with Bi-GRU for RUL estimation of EMR as shown in Fig. 1.

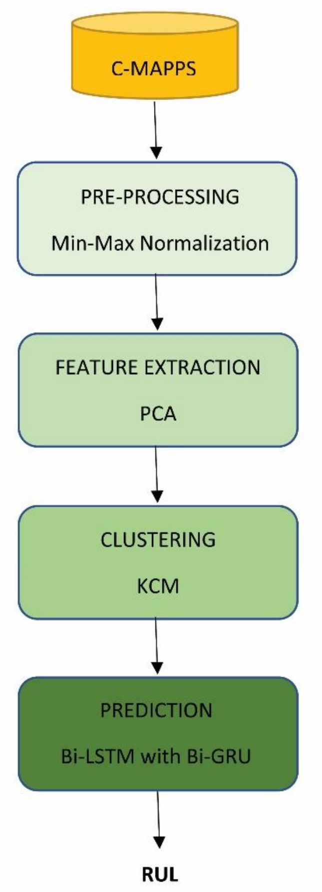

Fig. 1. Workflow of the suggested RUL prediction model

3.1. Pre-processing and Feature Extraction

PCA is a statistical model utilized for transforming a large group of parameters into a smaller one and retaining as more features as possible from the original set. The aim of PCA is to show differences and variances within the data and find patterns. In general, PCA is used to reduce dimension and it is used for screening the relation of features on sub-set of features. Although t-SNE and LDA were used to serve as a comparison for other dimension reductions, PCA was preferred since it can maximize variance that plays a key role in making the results of the cluster reliable. The orthogonal transformation is used for transforming the original features into a small set of features. This allows a reduced dataset to efficiently show the key information contained in the input data, hence achieving dimensionality reduction.

a) The initial step involves standardizing the dataset’s attributes to overcome biased results. To tackle the issue of inconsistent weights in data because of significant variation in the dimensions of sensitive features, the min-max normalization approach is deployed for normalizing the data. It is represented as:

$$w' = \frac{w - w_{\min}}{w_{\max} - w_{\min}} \tag{1}$$

where, w and w' are the original and normalized values; $w_{\min}$ and $w_{\max}$ are the minimum and maximum values.

b) The covariance matrix C_m of the w' is determined.

$$C_m = \sum_{j=1}^{n}\left((w_j - \mu)(w_j - \mu)^T\right) \tag{2}$$

where w_j and μ are parameter of dataset w' and mean vector.

c) The Eigen value λ_j of C_m and the respective Eigen vector v_j are computed and it is given as:

$$Av_j = \lambda_j v_j, \quad j = 1,2,...., n \tag{3}$$

d) The Eigen value is first principal component's $(PC1)$ variance and the Eigen vector is the transform matrix's column vector.

e) The Eigenvalues are arranged; the highest Eigenvalues are chosen and the respective Eigenvectors are utilized as row vectors for forming the Eigenvector matrix.

f) The data is transformed to the new value; the minimum and maximum normalization are carried out on the $PC1$. Preprocessing with the help of min-max normalization to make features play equally well for the process and then diminishing the biasing effects due to scales. Combining PCA has reduced computational complexity without an alteration in interpretability in transformed data. All data attributes were standardized to prevent biased outcomes and distribute equal weight during the process across all the features.

3.2. Clustering Process

K-means Clustering Algorithm is very efficient for partitioning of data with well-defined centers of clusters. It was therefore appropriate to identify homogeneous groups in the reduced PCA data. More over KMC does have excellent scalability with large datasets; this characteristic is important when applying multi-sensor data realized in the study. Other contenders were DBSCAN and hierarchical clustering but were not used since the size and complexity of the dataset was too large. The KMC is applied to PCA and the number of clusters is determined. Then, the data point is assigned to the clusters. Let us consider the m data points $\{y_1, y_{2,....y_m}\}$ in R^d, the process of reducing the variance in the dataset by splitting it into C clusters and it undergoes determining points $\{n_j\}$ in R^d.

$$\frac{1}{m}\sum_{i=1}^{m}\min_{g} d^2(y_i, n_j) \tag{4}$$

Here, the Equation (4) is minimized, $d(y_i, n_j)$ is the Euclidean distance among y_i and n_i. The points $\{n_j\}$ is cluster centroid. The aim of the Equation (4) is to identify C cluster centroid so that the mean square error among y_i, and the near n_j. The process of PCA and Clustering is shown in Fig. 2, and in Fig. 3, for plotting KMC using PCA components, $PC1$ and $PC2$ are the first two principal components derived from the original dataset. These components are linear combinations of the original features (columns) and are designed to capture the maximum variance in the data.

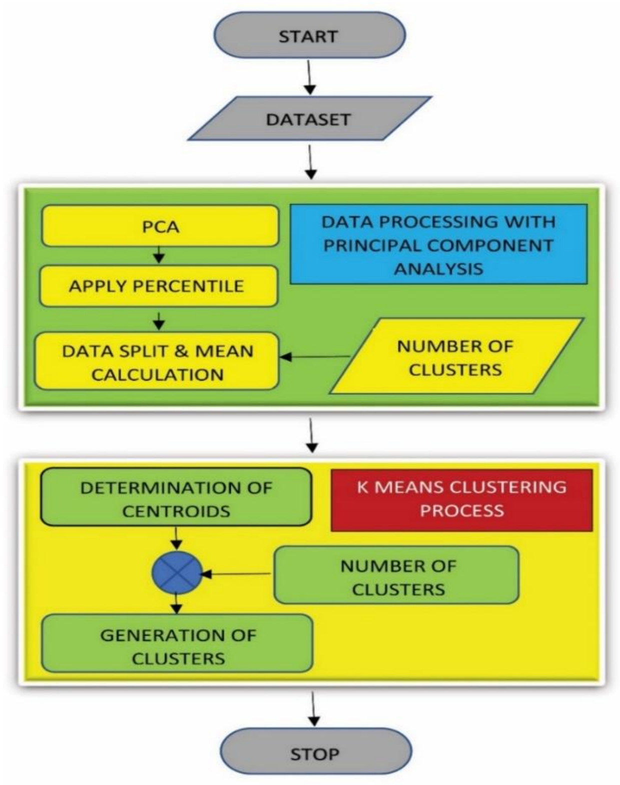

Fig. 2. PCA with KCM process flow diagram

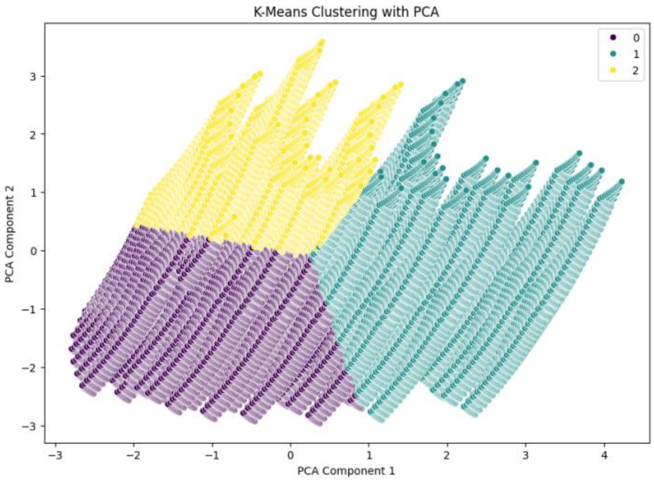

Fig. 3. PCA with KCM

3.3. RUL Prediction

After determining the cluster points, the DL model Bi-LSTM with Bi-GRU is used for predicting RUL for EMR. The parallel Bi-LSTM with Bi-GRU is used for capturing hidden features and proper RUL prediction for EMR. Fig, 4, states the structure of the Bi-LSTM with Bi-GRU. The multi- features extracted from KCM-PCA are fed into the Bi-LSTM with Bi-GRU network for obtaining multi-dimensionality features. These features from both networks are then integrated and fed into the regression layer for producing the prediction outcome. The BLSTM integrates different BLSTM layers to deeply extract the input data. Each pair of neighboring BLSTM layers is spatially connected to facilitate information transmission from the input to the output layer. Within every BLSTM layer, a bidirectional transmission model is developed, allowing the use of both past and future information. The main aim of BLSTM layers is the connecting between two LSTM layers with opposite directions (forward, backward) for generating the same output. Since it was capable of capturing both short-term and long-term dependencies in time-series data, the hybrid Bi-LSTM with Bi-GRU architecture was thus the selected model. The benefits of a chosen model accrue from the strength of the LSTM ability in dealing with long-range temporal dependencies while the efficiency of the GRU stays in the processing sequence with lesser parameters hence fast training with lesser overfitting. The hybrid approach becomes more robust in terms of prediction of RUL as compared to using LSTM or GRU alone.

It is mathematically expressed as:

$$H_{n,l}^{(P)} = \overrightarrow{H}_{n,l}^{(P)} \oplus \overleftarrow{H}_{n,l}^{(P)} \tag{5}$$

where, $\overrightarrow{H}_{n,l}^{(P)}$ and $\overleftarrow{H}_{n,l}^{(P)}$ are the LSTM's output for forward and backward at the n^{th} layer at the time l. The outcome of $\overrightarrow{H}_{n,l}^{(P)}$ is given as:

$$H_{n,l}^{(P)} = f\left(\overrightarrow{H}_{n,l-1}^{(P)}, \oplus X_{n,l}, \theta\right) \tag{6}$$

$$H_{n,l}^{(Q)} = \begin{cases} g_l = \phi\left(U_g\left[\overrightarrow{H}_{n,l-1}^{(P)}, \oplus X_{n,l}\right] + b_g\right) \\ i_l = \sigma\left(U_i\left[\overrightarrow{H}_{n,l-1}^{(P)}, \oplus X_{n,l}\right] + b_i\right) \\ f_l = \sigma\left(U_f\left[\overrightarrow{H}_{n,l-1}^{(P)}, \oplus X_{n,l}\right] + b_f\right) \\ o_l = \sigma\left(U_o\left[\overrightarrow{H}_{n,l-1}^{(P)}, \oplus X_{n,l}\right] + b_o\right) \end{cases} \tag{7}$$

where, $\overrightarrow{H}_{n,l-1}^{(P)}$ is the LSTM's output at time $l-1$, θ is parameter, U_g, U_i, U_f, U_o and b_g, b_i, b_f, b_o are weighting parameters and bias values. ϕ and σ are the tanh and activation function. In the Bi-GRU network, different Bi-GRU layers are combined and the same like the Bi-LSTM layers, Bi-GRU layers are also have forward and backward directions. The output of the Bi-GRU in the n Bi-GRU layer is represented as:

$$H_{n,l}^{(Q)} = \overrightarrow{H}_{n,l}^{(Q)} \oplus \overleftarrow{H}_{n,l}^{(Q)} \tag{8}$$

where $\overrightarrow{H}_{n,l}^{(Q)}$ and $\overleftarrow{H}_{n,l}^{(Q)}$ are the GRU's output for forward and backward at the n^{th} layer at the time l. the outcome of $\overrightarrow{H}_{n,l}^{(Q)}$ is given as:

$$H_{n,l}^{(Q)} = f\left(\overrightarrow{H}_{n,l-1}^{(Q)}, \oplus X_{n,l}, \theta\right) \tag{9}$$

$$H_{n,l}^{(Q)} = \begin{cases} Z_l = \sigma\left(U_g\left[\overrightarrow{H}_{n,l-1}^{(Q)}, X_{n,l}\right]\right) \\ R_l = \sigma\left(U_r\left[\overrightarrow{H}_{n,l-1}^{(Q)}, X_{n,l}\right]\right) \\ h_l = \phi\left(U_h\left[\overrightarrow{H}_{n,l-1}^{(Q)}, X_{n,l}\right]\right) \end{cases} \tag{10}$$

where, $\overrightarrow{H}^{(Q)}_{n,l-1}$ is the GRU's output at time $l-1$, θ is parameter, U_g, U_i, U_h, U_h and is the weighting parameters. ϕ and σ are the tanh and activation function.

The concatenation layer is used for combining the hidden features from the networks like Bi-LSTM layers and Bi-GRU layers. It is given as:

$$H_l = \left[H^{(P)}_{n,l}, H^{(Q)}_{n,l}\right] \tag{11}$$

At last, the regression layer is used for capturing feature maps and the RUL $\hat{r}_l$ of EMR is predicted as:

$$\hat{r}_l = H_l U_r \tag{12}$$

where U_r is the regression layer's weight.

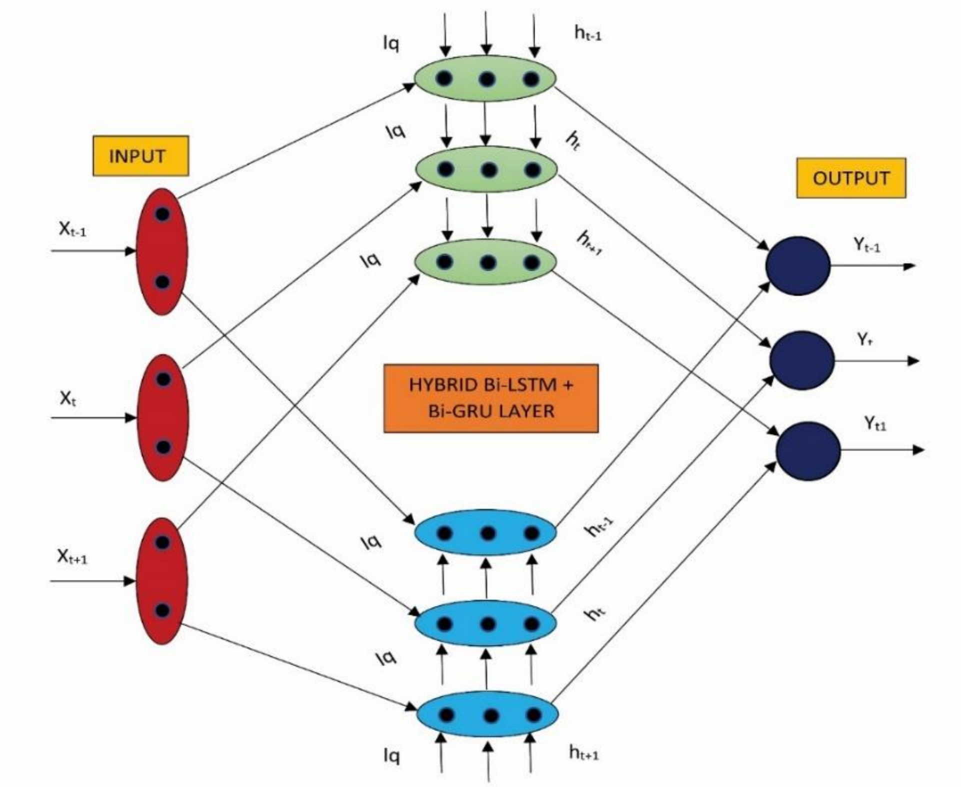

Fig. 4. The structure of Bi-LSTM with Bi-GRU

4. Results and Discussions

The following section states the results outcomes of the suggested RUL for EMR. The experimentation is demonstrated on the Python platform. The outcomes of the suggested Bi-LSTM with Bi-GRU are compared over the DL models like RNN, LSTM, GRU, Bi-LSTM, Bi-GRU models. The mean square error (MSE), root MSE (RMSE), mean absolute error (MAE) and R-squared (R^2). Table 1 delineates the expressions for computing the RUL.

Table 1 - Expressions for computing the RUL

Metrics	Expressions
MSE	$\frac{1}{p}\sum_{q=1}^{p}\left(y_q - \hat{y}_q\right)^2$
RMSE	$\sqrt{\frac{1}{p}\sum_{q=1}^{p}\left(y_q - \hat{y}_q\right)^2}$

MAE	$\frac{1}{p}\sum_{q=1}^{p}\left\| y_q - \hat{y}_q \right\|$
R^2	$1-\frac{\sum_{q=1}^{p}\left(y_q-\hat{y}_q\right)^2}{\sum_{q=1}^{p}\left(y_q-\overline{y_q}\right)^2}$

where, y_q and $\hat{y}_q$ are actual and observed RUL values; q is the overall observations and $\overline{y_q}$ is the mean actual values.

4.1. Dataset Detail

The suggested work is assessed using a prognostic dataset Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) program, and NASA introduced this dataset. It has a dataset that includes four sub-sets, each consisting of multivariate temporal data from twenty-one sensors. Every sub-set has both training as well as a test set. The training set consists of run to failure sensor records from multi aero-engines, obtained by several operating conditions and fault conditions. Every engine unit is initiated by various levels of initial wear and manufacture difference, which are not known and set to be in a healthy stage. As time passes, the engines degrade till they undergo system failures, with the final data entry representing the cycle at which the engine is deemed unhealthy. Conversely, the sensor records in the test datasets end at a point before failure in the network, and the objective is for estimating the RUL of every engine in the test set. The original values of RUL for the test engine units are offered for validation purposes. This work conducted a series of evaluation of the suggested RUL over every four sub-sets (FD001, FD002, FD003, and FD004).

4.2. Comparative Analysis

The performance of the suggested Bi-LSTM with Bi-GRU is compared over the DL models like Bi-GRU, GRU, Bi-LSTM, LSTM, and RNN models. Table 2, and corresponding and Fig 5 to Fig 8 defines the comparative analysis on the four set like FD001, FD002, FD003, and FD004. It is observed from the Table that the all-comparative measures on all datasets achieved better MSE, RMSE, MAE and R^2 and outperformed other models.

Table 2 - Comparative Analysis.

FD001				
Methods	MSE	RMSE	MAE	R^2
Bi-LSTM + Bi-GRU	0.002	0.001	0.100	0.983
Bi-GRU	0.004	0.02	0.103	0.947
GRU	0.007	0.03	0.130	0.923
Bi-LSTM	0.004	0.02	0.121	0.931
LSTM	0.008	0.04	0.245	0.901
RNN	0.123	0.051	0.234	0.892
FD002				
Methods	MSE	RMSE	MAE	R^2
Bi-LSTM + Bi-GRU	0.001	0.005	0.021	0.996
Bi-GRU	0.007	0.02	0.074	0.978
GRU	0.124	0.03	0.141	0.943
Bi-LSTM	0.112	0.02	0.098	0.954
LSTM	0.152	0.031	0.152	0.913
RNN	0.171	0.032	0.171	0.896
FD003				
Methods	MSE	RMSE	MAE	R^2
Bi-LSTM + Bi-GRU	0.003	0.004	0.021	0.993
Bi-GRU	0.004	0.01	0.081	0.971
GRU	0.005	0.033	0.135	0.935
Bi-LSTM	0.004	0.01	0.091	0.939
LSTM	0.009	0.041	0.138	0.915
RNN	0.143	0.041	0.149	0.884

FD004				
Bi-LSTM + Bi-GRU	0.004	0.043	0.023	0.983
Bi-GRU	0.009	0.041	0.071	0.947
GRU	0.131	0.033	0.134	0.923
Bi-LSTM	0.123	0.022	0.092	0.931
LSTM	0.145	0.058	0.145	0.901
RNN	0.241	0.052	0.147	0.892

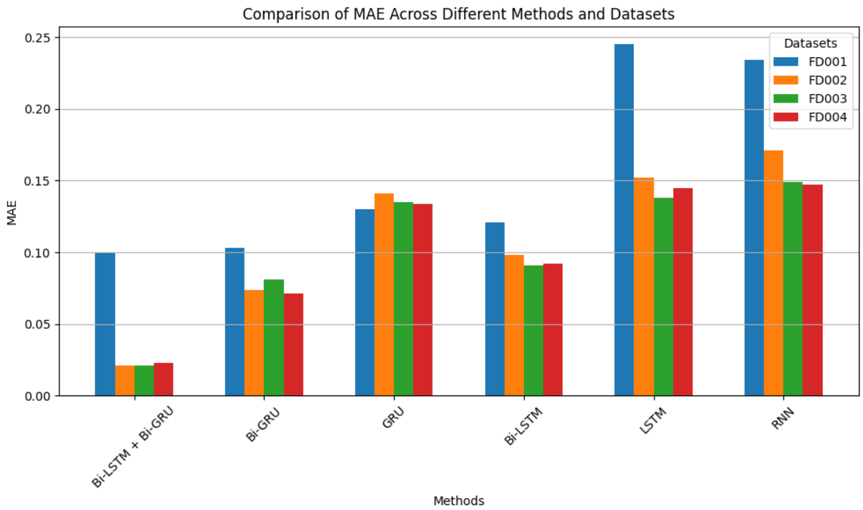

Fig. 5. Comparision MAE across different models

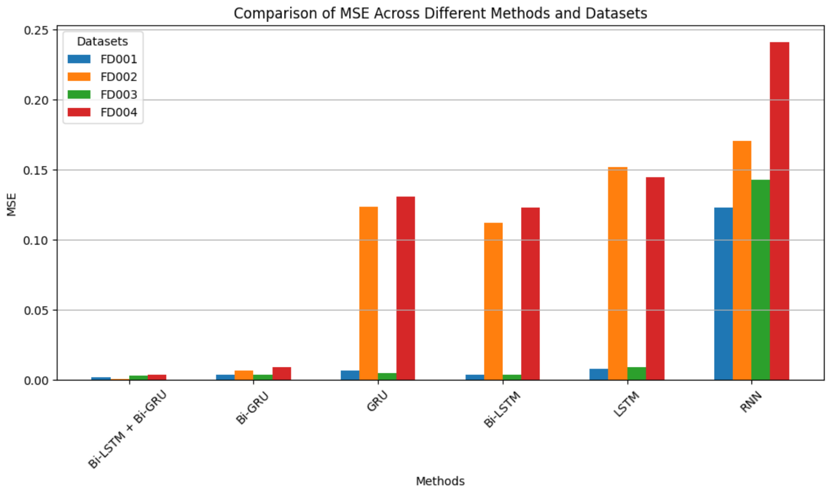

Fig. 6. Comparision MSE across different models

Fig. 7. Comparision of R2 across different models

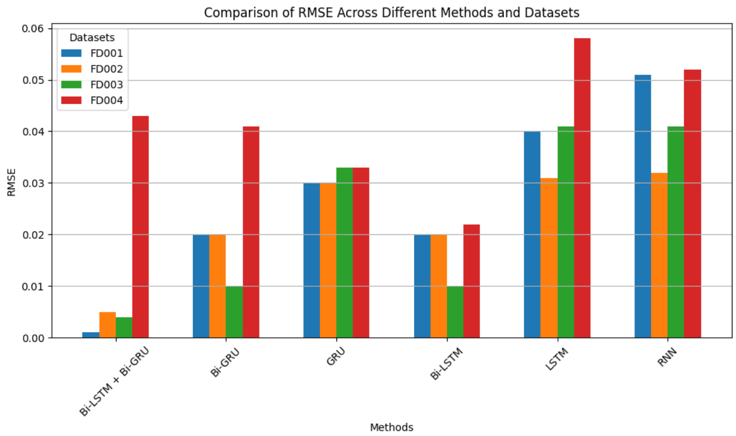

Fig. 8. Comparision RMSE across different models

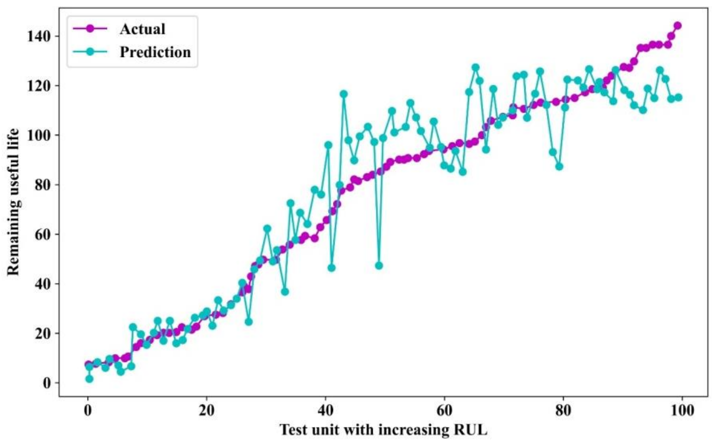

Fig. 9. Testing data with respect to RUL

Fig. 9, states the prediction of RUL outcomes for the test engine units in C-MAPSS, based on the final data-point. For enhanced clarification and analysis, the test engine units are sorted in ascending order with respect to their labels. It is proved that the RUL values predicted by the suggested Bi-LSTM with Bi-GRU are generally near the actual values.

Fig. 10, defines the prediction of RUL outcomes for the time (Cycle) in C-MAPSS. The time cycle is varied between 1 to 175 and the RUL values are plotted for suggested Bi-LSTM with Bi-GRU. As the number of cycles increases, the RUL typically decreases, and it indicates the Bi-LSTM with Bi-GRU's degradation over time. It is noted that the RUL value is stable for 50 times (cycle) and it decreased after the 50 times (cycle).

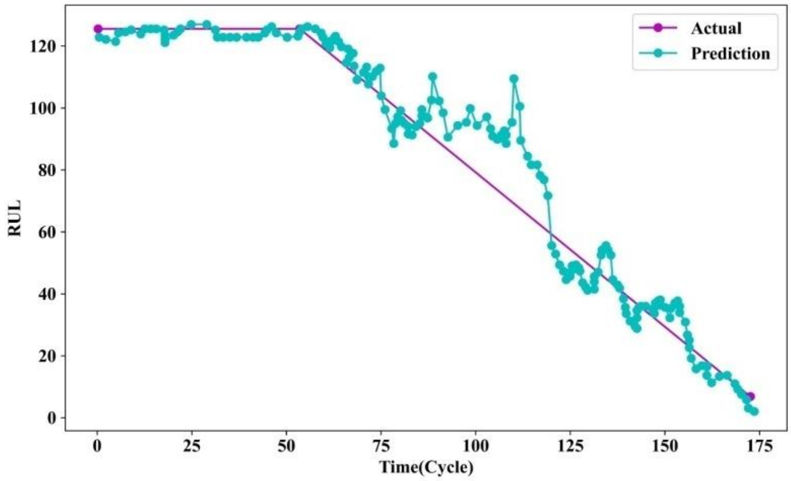

Fig. 10. Time (cycle) with respect to RUL

5. Conclusion

This work presented an efficient model for predicting the RUL of EMR by integrating KMC-PCA with a hybrid Bi-LSTM with Bi-GRU. The major stage involved the extraction of multiple degradation features from C-MAPSS, dimensionality reduction using PCA, and the KMC was used to find various operational states. The hybrid Bi-LSTM with Bi-GRU effectively captured the features and RUL prediction. Here, the PCA effectively minimized the dataset's complexity and retained critical information. Then, the KMC assists in finding various degradation states and failure modes, which are essential to maintain the underlying behaviour of the relays. The suggested Bi-LSTM with Bi-GRU considered the advantages of both BLSTM and BGRU architectures, and it results in better and more robust RUL predictions compared to other DL models. Future work may focus on extending this suggested methodology will be applied to other kinds of components and integrating additional environmental and operational factors for refining the prediction of RUL.

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References

An, B., Wang, S., Yan, R., Li, W., & Chen, X. (2020). Adaptive robust noise modeling of sparse representation for bearing fault diagnosis. *IEEE Transactions on Instrumentation and Measurement*, *70*, 1-12. https://doi.org/10.1109/TIM.2020.3039648

Deutsch, J., & He, D. (2017). Using deep learning-based approach to predict remaining useful life of rotating components. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *48*(1), 11-20. https://doi.org/10.1109/TSMC.2017.2697842

Ding, X., & He, Q. (2017). Energy-fluctuated multiscale feature learning with deep convnet for intelligent spindle bearing fault diagnosis. *IEEE Transactions on Instrumentation and Measurement*, *66*(8), 1926-1935. https://doi.org/10.1109/TIM.2017.2674738

Fink, O., Wang, Q., Svensen, M., Dersin, P., Lee, W. J., & Ducoffe, M. (2020). Potential, challenges and future directions for deep learning in prognostics and health management applications. *Engineering Applications of Artificial Intelligence*, *92*, 103678. https://doi.org/10.1016/j.engappai.2020.103678

Gan, C. L. (2020). Prognostics and Health Management of Electronics: Fundamentals, Machine Learning, and the Internet of Things: John Wiley & Sons Ltd.(2018). pp. 731, ISBN:

9781119515326 (Print), 9781119515326 (Online). *Life Cycle Reliability and Safety Engineering*, *9*(2), 225-226. https://doi.org/10.1007/s41872-020-00119-y

Ghahramani, M., Qiao, Y., Zhou, M. C., O'Hagan, A., & Sweeney, J. (2020). AI-based modeling and data-driven evaluation for smart manufacturing processes. *IEEE/CAA Journal of Automatica Sinica*, *7*(4), 1026-1037. https://doi.org/10.1109/JAS.2020.1003114

Hu, X., Wei, X., Ma, Y., & Liu, Z. (2023, October). Research on the Health State Assessment of Electromagnetic Relays Based on PSO-SVM-DS. In *International Conference on Electrical and Information Technologies for Rail Transportation* (pp. 558-566). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-99-9315-4_54

Khater, M. A. (2020). High-speed printed circuit boards: A tutorial. *IEEE Circuits and Systems Magazine*, *20*(3), 34-45. https://doi.org/10.1109/MCAS.2020.3005484

Kirschbaum, L., Robu, V., Swingler, J., & Flynn, D. (2022). Prognostics for electromagnetic relays using deep learning. *IEEE Access*, *10*, 4861-4895. https://doi.org/10.1109/ACCESS.2022.3140645

Kirschbaum, L., Roman, D., Singh, G., Bruns, J., Robu, V., & Flynn, D. (2020). AI-driven maintenance support for downhole tools and electronics operated in dynamic drilling environments. *IEEE Access*, *8*, 78683-78701. https://doi.org/10.1109/ACCESS.2020.2990152

Lei, Y., Li, N., Guo, L., Li, N., Yan, T., & Lin, J. (2018). Machinery health prognostics: A systematic review from data acquisition to RUL prediction. *Mechanical systems and signal processing*, *104*, 799-834. https://doi.org/10.1016/j.ymssp.2017.11.016

Leung, C. H., & Lee, A. (1991). Contact erosion in automotive DC relays. *IEEE transactions on components, hybrids, and manufacturing technology*, *14*(1), 101-108. https://doi.org/10.1109/33.76517

Li, B., Bian, Z., & Wang, Z. (2021). Research on the electric life prediction of relay contact based on harris hawk optimized. *IEEE Transactions on Instrumentation and Measurement*, *71*, 1-10. https://doi.org/10.1109/TIM.2021.3135550

Li, X., Ding, Q., & Sun, J. Q. (2018). Remaining useful life estimation in prognostics using deep convolution neural networks. *Reliability Engineering & System Safety*, *172*, 1-11. https://doi.org/10.1016/j.ress.2017.11.021

Liu, J., Zhang, M., Zhao, N., & Chen, A. (2018). A reliability assessment method for high speed train electromagnetic relays. *Energies*, *11*(3), 652. https://doi.org/10.3390/en11030652

Liu, L., Chen, Z., Yang, W., Zhai, G., Zio, E., & Kang, R. (2024). A novel methodology for the optimization of design parameters of electromagnetic relays. *Nonlinear Dynamics*, *112*(4), 2909-2932. https://doi.org/10.1007/s11071-023-09189-w

Motahari-Nezhad, M., & Jafari, S. M. (2023). Comparison of MLP and RBF neural networks for bearing remaining useful life prediction based on acoustic emission. *Proceedings of the Institution of Mechanical Engineers, Part J: Journal of Engineering Tribology*, *237*(1), 129-148. https://doi.org/10.1177/13506501221106556

Pecht, M., Mathew, S., & Gullo, L. J. (1856). 'IEEE standard framework for prognostics and health management of electronic systems. *IEEE Standards Assoc., Piscataway, NJ, USA, Tech. Rep*, *2017*, 2017.

Qin, Y., Yuen, C., Shao, Y., Qin, B., & Li, X. (2022). Slow-varying dynamics-assisted temporal capsule network for machinery remaining useful life estimation. *IEEE Transactions on Cybernetics*, *53*(1), 592-606. https://doi.org/10.1109/TCYB.2022.3164683

Robu, V., Flynn, D., & Lane, D. (2018). Train robots to self-certify their safe operation. *Nature*, *553*(7688).

Roman, D. V., Dickie, R. W., Flynn, D., Robu, V., Cepin, M., & Briš, R. (2017). A review of the role of prognostics in predicting the remaining useful life of assets: 27th European Safety and Reliability Conference, ESREL 2017. https://doi.org/10.1201/9781315210469-116

Roman, D., Saxena, S., Bruns, J., Valentin, R., Pecht, M., & Flynn, D. (2021). A machine learning degradation model for electrochemical capacitors operated at high

temperature. *IEEE Access*, *9*, 25544-25553. https://doi.org/10.1109/ACCESS.2021.3057959
Roman, D., Saxena, S., Robu, V., Pecht, M., & Flynn, D. (2021). Machine learning pipeline for battery state-of-health estimation. *Nature Machine Intelligence*, *3*(5), 447-456. https://doi.org/10.1038/s42256-021-00312-3
Sateesh Babu, G., Zhao, P., & Li, X. L. (2016). Deep convolutional neural network based regression approach for estimation of remaining useful life. In *Database Systems for Advanced Applications: 21st International Conference, DASFAA 2016, Dallas, TX, USA, April 16-19, 2016, Proceedings, Part I 21* (pp. 214-228). Springer International Publishing. https://doi.org/10.1007/978-3-319-32025-0_14
Saxena, A., Celaya, J., Saha, B., Saha, S., & Goebel, K. (2010). Metrics for offline evaluation of prognostic performance. *International Journal of Prognostics and health management*, *1*(1), 4-23.
Sun, Y., Cao, Y., Zhang, Y., & Xu, C. (2018). A novel life prediction method for railway safety relays using degradation parameters. *IEEE Intelligent Transportation Systems Magazine*, *10*(3), 48-56. https://doi.org/10.1109/MITS.2018.2842048
Verstraete, D., Ferrada, A., Droguett, E. L., Meruane, V., & Modarres, M. (2017). Deep learning enabled fault diagnosis using time-frequency image analysis of rolling element bearings. *Shock and Vibration*, *2017*(1), 5067651. https://doi.org/10.1155/2017/5067651
Wang, Y., Zhao, Y., & Addepalli, S. (2020). Remaining useful life prediction using deep learning approaches: A review. *Procedia manufacturing*, *49*, 81-88. https://doi.org/10.1016/j.promfg.2020.06.015
Winkel, F., Deuse-Kleinsteuber, J., & Böcker, J. (2023). Run-to-failure relay dataset for predictive maintenance research with machine learning. *IEEE Transactions on Reliability*, *73*(1), 101-114. https://doi.org/10.1109/TR.2023.3255786
Yang, J., Nguyen, M. N., San, P. P., Li, X., & Krishnaswamy, S. (2015, July). Deep convolutional neural networks on multichannel time series for human activity recognition. In *Ijcai* (Vol. 15, pp. 3995-4001).
Yin, X., & Huang, B. (2022). Event-triggered distributed moving horizon state estimation of linear systems. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *52*(10), 6439-6451. https://doi.org/10.1109/TSMC.2022.3146182
Yin, X., & Liu, J. (2020). Event-triggered state estimation of linear systems using moving horizon estimation. *IEEE Transactions on Control Systems Technology*, *29*(2), 901-909. https://doi.org/10.1109/TCST.2020.2978908
Yuming, H., Jiaohong, L., Zhenguo, M., Bing, T., Keqi, Z., & Jianyong, Z. (2023). On combined PSO-SVM models in fault prediction of relay protection equipment. *Circuits, Systems, and Signal Processing*, *42*(2), 875-891. https://doi.org/10.1007/s00034-022-02056-w
Zeiler, M. D. (2014). Visualizing and Understanding Convolutional Networks. In *European conference on computer vision/arXiv* (Vol. 1311). https://doi.org/10.1007/978-3-319-10590-1_53
Zhang, X., Qin, Y., Yuen, C., Jayasinghe, L., & Liu, X. (2020). Time-series regeneration with convolutional recurrent generative adversarial network for remaining useful life estimation. *IEEE Transactions on Industrial Informatics, 17*(10), 6820-6831. https://doi.org/10.1109/TII.2020.3046036
Zhao, Y., Zio, E., & Fu, G. (2017). Remaining storage life prediction for an electromagnetic relay by a particle filtering-based method. *Microelectronics Reliability*, *79*, 221-230. https://doi.org/10.1016/j.microrel.2017.03.026
Zheng, S., Ristovski, K., Farahat, A., & Gupta, C. (2017, June). Long short-term memory network for remaining useful life estimation. In *2017 IEEE international conference on prognostics and health management (ICPHM)* (pp. 88-95). IEEE. https://doi.org/10.1109/ICPHM.2017.7998311
Zheng, Y., Liu, Q., Chen, E., Ge, Y., & Zhao, J. L. (2014, June). Time series classification using multi-channels deep convolutional neural networks. In *International conference on*

web-age information management (pp. 298-310). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-08010-9_33

Zheng, Y., Liu, Q., Chen, E., Ge, Y., & Zhao, J. L. (2016). Exploiting multi-channels deep convolutional neural networks for multivariate time series classification. *Frontiers of Computer Science*, *10*, 96-112. https://doi.org/10.1007/s11704-015-4478-2.