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A novel survival analysis of machine using fuzzy ensemble convolutional based optimal RNN

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ABSTRACT

Survival Analysis is essential in the manufacturing field to determine unnecessary events by the input data. In Survival analysis, predictive maintenance plays a major portion in the identification of machine failures based on incoming input data from diverse equipment or sensors. Therefore, the Deep learning method is exploited for barbarizing the issues of predictive maintenance marginally but these techniques are not quite useful to predict the failure of devices for certain input data which the technique had not learned. Meanwhile, the neural network techniques are capable of predicting the output in accordance with the preceding input feature, the performance was poor when the input features have large variations. As a result, the transformation of input data degrades the performance of the neural network and the algorithm does not support the prediction of machine failure. To overcome such drawback, this paper proposes a novel Sugeno Fuzzy Ensemble Convolutional based War Strategy Algorithm (SFEC-WSA) to classify the device and identify the survival time in accordance with the input features. The proposed SFEC system integrates the process of both the Sugeno fuzzy integral ensemble model and the Attention-based Bidirectional CNN-RNN Deep Model (ABCDM). The SFEC-WSA algorithm is applicable in learning diverse input feature variations thereby predicting the robustness of the input data. The proposed SFEC-WSA analyses several parameters such as vibration, rotation, voltage, and pressure to evaluate the condition of the equipment. The experimentation results revealed that the proposed model effectively predicts large test data and performs better than other approaches.

1. Introduction

Nowadays, the emergence of information in technology is one of the most important ones for all people. Data is the word mainly used in the entire field such as the medical, financial, and industrial sectors. Big data plays a major role that changing the environment of the medical healthcare sector. The big data are gathered from the patients and saved digitally which helps the patients for better care and services. Big data cannot manage with database management tools that contain difficulty as well as enormous characteristics. The fundamental method of medicine is the calculation analysis of combined databases (Yang et al., 2020). Survival Analysis is the numerical form of analysis used to identify the specific duration of an event that is going to happen and provides to manage the risk of that particular event. The survival analysis is used by doctors for making screening decisions and provides treatment for alleviating the risk of diseases in humans. The deep neural network helps in the field of analysis, especially in survival analysis. This method focuses on handling the situations of multiple events and learning the difficult situations among possibilities of survival and trajectories (Lee et al., 2019).

Meta-analysis recommended that thrombolysis decreases the death rate of patients but increases intracranial hemorrhage and bleeding (Javaudin et al., 2019). Moreover, the immune system consists of T and B cells. The B cells confinement is called a Tertiary Lymphoid structure (TLS) which is found in melanoma and various types of cancer. From the analysis of melanoma tumors, $cd8^{+}T$ cell infiltration is 33% of patients. The survival of $TLS/cd8^{+}$ continues in the multivariate analysis for the stage of the disease. The lymph node metastases by using survival

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analysis identified the patient's trend including tumor-infiltrative TLS with enhanced survival (Cabrita et al. 2020). Another disease is Coronavirus which is a vulnerable disease spread all over the world (Kannan et al., 2021). Also, the 331,298 patients' data were analyzed, and found positive cases of covid-19 were by using real-time Polymerase Chain reaction (PCR) (Parra-Bracamonte et al. 2020). Breast cancer is a diagnosed disease that leads to death. The therapeutic effects are improved by chemotherapy and surgery for breast cancer (Sun et al., 2019).

In cancer clinical trials, the patient's voice was included when evaluating the risk present in cancer by PROs (Patient-Reported Outcomes). The PROs are clinically analyzed and they provide information about the safety of patients, and choices of treatment (Coens et al., 2020). The statistical methods are not helpful for the identification of new values and visualizations. The decision tree analyses the big data for the illustration of the result and interprets the tree structure. In the survival analysis, the survival years of dead ones are commutated by the subtraction of the diagnosis date to the death date (Ganggayah et al., 2019). The combined genomic data and histopathological images improved the survival predictions and personalized treatments (Hao et al., 2019).

The decisions made in the Intensive Care Unit (ICU) improved the prognostication of patients' risk of dying. Several proclaimed methods found in ICU were Simplified Acute Physiology Assessment, Acute Physiology Score (SAPS), mortality prediction model, and chronic health evaluation. The ICU provides valuable information based on the outcomes of the patient but some information gathers from ICU is not regular. Machine learning technologies provide clear data and help in clinical decision-making (Thorsen-Meyer et al., 2020). The Machine Learning techniques applied to many neural networks along with parameters are optimized (Huang et al., 2019).

Yang et al.(2023) presented a meta-graph-based fault diagnosis framework to identify the faults in homogeneous sensors. The features in the graph are learned using the graph convolutional neural network. Asutkar et al.(2023) presented a transfer learning framework for identifying the faults and survival rate of vibration-based machines. Lao et al.(2023) presented a Dual Scale Neural Network (DSNN) to extract the fault features which affect the survival rate of the switch machines. To handle the unannotated samples, the semi-supervised weighted prototypical network (SSWPN) model is presented. Lao et al.(2023) analyzed the survival rate of the turnout switch machine using an improved LightGBM (Light Gradient Boosting Machine) architecture optimized using the adaptive feature selection method and improved focal loss function. These techniques are mainly incorporated to overcome the low diagnostic accuracy of the existing techniques, discriminate similar features, and minimize redundant features.

In deep neural networks, the survival time using Weibull distribution is analyzed for large datasets. The Cox proportional hazards regression technique is used to analyze the censored data. Due to the presence of hazard function the survival time of the proportional hazards remains stable (Zhao and Feng, 2020). The survival analysis of detection is the statistical model which is widely utilized in clinical applications. The survival analysis is evaluated based on the functions of survival and hazard. The main issue obtained in the survival analysis is it is not able to maintain the data within the given time (Deepa & Gunavathi, 2022). To analyze large industrial data, multi-sensor data is introduced to obtain the machine's data in the form of electronic record management. This helps to validate the data records scientifically from the previously obtained unknown data (Sankareswaran Pandi Senthil & Krishnan Mahadevan, 2022). Machine learning and deep learning methods are determined in survival analyses for predicting the disorder (Almazroi, 2022).

In the Sugeno Fuzzy Ensemble Convolution method, the analysis of fuzzy is optimally determined with better classification. It is widely used in the engineering field for modeling and also controls complex systems. The complex problems obtained in various engineering fields are solved by this method and enhance the performance of survival analysis (Dhiravidachelvi et al., 2023; Kalpana et al., 2023; Senthil Pandi et al., 2022a, 2022b).

The Sugeno fuzzy ensemble technique is utilized in this paper instead of the conventional fuzzy ensemble techniques because it determines the overall outcome of the input test sample using different combinations of the CNN classifier output. Here the final classification score is determined using the fuzzy membership function instead of the CNN prediction scores. The effective ABCDM model is utilized to enhance the feature extraction ability of the proposed model at different scales from the machine. The WSA algorithm is used to fine-tune the SFEC model to improve the faults diagnosis and survival rate prediction ability. The SFEC model has a superior distinguishing ability to detect faults in the machinery.

The integration of these techniques helped to improve the generalization and robustness of the node survival analysis model. Various researchers utilized the Sugeno fuzzy ensemble technique for different applications such as COVID-19 prediction (Dey et al., 2022), imbalanced data analysis (Wang et al., 2020), motor imagery classification (Zhang and Ding, 2023), cervical cytology classification (Kundu et al., 2021), tuberculosis detection (Dey et al., 2022), etc. Our proposed model is the first one which applies the Sugeno fuzzy ensemble technique for machine survival rate analysis inspired by its advantages of it in other domains. Due to the continuous enhancement of the Sugeno fuzzy ensemble convolution approach, this can be applied in the manufacturing field by proposing the SFEC-WSA method. Compared to the previous method the proposed method attained a superior performance in survival analysis and also predicted large datasets.

The prediction of a faulty framework is complex to identify input data combination that leads to failure. For this problem, a novel technique is proposed in this paper to enhance the performance of input features containing large variations. The contribution of this paper is delineated as follows.

- A novel Sugeno Fuzzy Ensemble Convolutional based War Strategy Algorithm (SFEC-WSA) algorithm is proposed to predict the failure of the device and identify the survival time based on input data.
- The proposed SFEC system integrates the process of both the Sugeno fuzzy integral ensemble model and the Attention-based Bidirectional CNN-RNN Deep Model (ABCDM) to determine varied features of the data for enhancing prediction results.
- The proposed SFEC-WSA analyses several parameters such as vibration, rotation, voltage, and pressure to evaluate the condition of equipment thereby predicting the robustness in accordance with the input data.
- The parameters such as accuracy, precision, recall, and F1-score are obtained to validate the performance of the proposed method.

The remaining part of the article is delineated as follows. In section 2, the existing works based on the Survival analysis of structured data using various methods are discussed. In section 3, the proposed approach for survival analysis is described. The experimental results are presented in section 4. Finally, in section 5, the conclusion part is discussed in this paper.

2. Literature survey

Warrier and Gupta (2022) developed using deep reinforcement learning to analyze survival on structured data. Prediction of the survival device on the input data was a difficult task because of its lack of failure data capturing and the occurrence was very rare. The deep learning algorithm called the Double deep Q network (DDQN) model was introduced in this paper to classify the failure device. As a result, the introduced DDQN model was trained through the smaller quantity of input data as well as efficiently predicted a larger quantity of test data. Meanwhile, the same analysis was needed to implement image data modality. Thorsen et al. (2022) illustrated a deep learning method to estimate the survival analysis of discrete time. The main subjective of this paper was for predicting the patient's survival based on the intensive care unit (ICU). A deep learning design was introduced in this paper to estimate the data-rich settings through survival modeling and entity embeddings in the ICU. Using the SHAP method to calculate and visualize drivers of survival predictions. Therefore, the interpretability models enable us for understanding the various data domains impacts.

Chi et al. (2021) established a survival analysis description using the deep semi-supervised multitask learning (SSMTL) method. Survival analysis has been used to predict and analyze the timing of events in the medical field. But some assumptions are ignoring real-world data. In this paper, SSMTL was introduced for tackling the issues, and the effects of predictors are described successfully. As a result, the SSMTL method attains to enhance the performance and the survival analysis setting in with or without competing risks. On the other hand, this method cannot handle all complex tasks in machine learning. Kopper et al. (2022) explained a survival analysis of complex hazard structures using Deep Piecewise exponential Additive Mixed Models (DPAMM). Survival analysis has become prevalent in many medical applications. To address the time-to-event in the medical field, DPAMM was introduced in this paper. Hence, compared to other machine learning techniques DPAMM achieved better performance for predictive. However, in high dimensional data or multimodal data, the introduced PAMM method was not applicable.

Chi et al. (2021) illustrated survival analysis and explanation of the semi-supervised learning model. The SSMTL method was obtained for analysis with or without taking a risk. The survival analysis problem could be converted into a multi-task problem by the SSMTL method. The survival analysis model could be directly modeled without any supposition. The survival analysis of the deep learning method was effectively used in complex situations that occurred in the medical field. As a result, the survival analysis of the SSMTL model obtained a better performance. The prognostic factors were obtained successfully. On the other hand, the outcome iterations were unstable. Lee et al. (2019) illustrated the deep learning approach obtained to challenge the risk for dynamic survival analysis. The dynamic deep-hit approach was applied which avoided the risks based on longitudinal data. As a result, the established method of dynamic analysis on disease progression improved health care effectively. The individual risks obtained from cystic fibrosis failures could be improved highly by a dynamic deep-hit approach. Meanwhile, it required a long time to link the other national data set.

Snider and McBean (2020) reviewed the improvement of urban water scarcity through machine learning (ML) techniques. In the Canadian water distribution system, the Weibull proportional hazard survival analysis design and tree ML design was used for prognosticating the time for cast-iron pipes. The two-pipe break designing approaches survival analysis and MLalgorithm were applied. As a result, the machine learning algorithm was good which predicted the time-to-break dataset in the indicators such as MAE, RMSE, C-index, and correlation. Meanwhile, the prediction of pipe-break designs was not improved and the cost was effective. Seidler et al. (2019) illustrated cervical lymphadenopathy evaluation in machine learning techniques of dual-energy CT analysis. The VMI (Virtual Monochromatic Image) dataset was used which differentiated the head and neck squamous cell carcinoma (HNSCC). As a result, the texture analysis with different nodal pathology was obtained with higher accuracy. On the other hand, two separate image data sets were required for analysis.

Survival analysis is a significant method that is used in the manufacturing field to calculate the time variations of events. The failures of the machines are determined based on the incoming data from various sensors and equipment. To determine the survival analysis the authors explained various research methods. Some of the existing methods such as SSMTL, DDQN, DPAMM, HNSCC, and various machine learning methods are employed to overcome the issue obtained in detecting the input data from the failed device. The survival analysis data are predicted based on the data-rich settings. In the medical field, survival analysis is used to detect the disease on time which helps to tackle time consumption. To overcome the complex situations generated in the industrial field the survival analysis is determined. However, all these developed methods have some limitations in that they validated the data only when two different data and data modalities are obtained in survival analysis. When redundant data is obtained it is not able to handle the data in machine learning methods. In some situations, the survival analysis is not suitable for high-dimensional data.

The multiple sensor data can often give information about the faults in different parts of the machine which affects its survival rate. Hence, one of the challenges associated with the existing technique is to determine the high-quality features present in the multi-sensor data. The existing graph-based techniques often complicate this process by creating a complex graph structure to process the multidimensional data resulting in large computational costs. Most of the existing research is mainly focused on identifying a single type of fault in the rotating machines. Different parameters such as vibration, current, and temperature also need to be explored to derive the complete status of the machinery. To integrate the multi-sensor data for fault diagnosis, we incorporated different parameters such as rotation, voltage, vibration, and pressure.

So the drawbacks of the existing methods are overcome by the proposed Sugeno Fuzzy Ensemble Convolutional-based War Strategy Algorithm (SFEC-WSA) for categorizing the system to identify the survival time. The proposed method is suitable for varied applications of input data features that validate the failure of equipment. Multiple data are processed by optimizing the WSA algorithm that improved the effectiveness of survival analysis. The unbalanced data are determined to estimate the survival analysis of the structured data. This work mainly aims to analyze the survival rate of the machinery based on the different features identified. Based on the machinery's condition and the cost to repair it will determine the survival rate of the machine. Early failure can be detected and the survival rate can be improved via a proper maintenance tactic.

2.1. War Strategy Optimization (WSO)

Based on the fitness value, the soldiers had an equal probability of becoming either commander or king in every iteration. In the war field, the commander and king act as the leaders, and the remaining soldiers are guided by the commander and king. The infantry, elephants, and chariots are the several forces in the kingdom's army. The Vyuha is the arrangement or pattern of several army troops utilized for conquering the opposing kingdoms in the war. The main objective of the army soldier is for attacking the opposite team as well as order progress. In war strategy, various steps are involved and they are followed (Ayyarao et al. 2022);

2.1.1. Attack strategy

According to the position of commander and king, the soldiers are updating their positions. The king assumed the beneficial position for launching massive attacks based on position. The soldiers with the highest attack fitness or force are considered the king. If the strategy was successfully performed by a soldier, his rank increases. The weights and ranks of the soldiers are updated by the success of the strategy.

$$Z_k(v+1) = Z_k(v) + 2 \times \beta \times (E - \mathrm{K}) + \Re and \times (X_k \times \mathrm{K} - Z_k(v)) \tag{1}$$

where $Z_k(v+1)$ denotes the new position, the previous E position is indicated by Z_k, king position is represented by K, as well as weights are indicated by W_k.

2.1.2. Update weight and rank

The search agents updated their position based on the position interaction of the commander, King as well as the rank of every soldier. In the war field, the soldier's rank will be based on their success history. Then the mathematical calculation is expressed as;

$$Z_k(v+1) = (Z_k(v+1)) \times (H_p \geq H_r) + (Z_k(v)) \times (H_p < H_r) \tag{2}$$

When the soldiers are updated their position successfully, then the soldier is upgraded their rank S_k and it is expressed as;

$$S_k = (S_k + 1) \times (H_p \geq H_r) + (S_k) \times (H_p < H_r) \tag{3}$$

The newly generated weight is formulated as;

$$X_k = X_k \times \left(1 - \frac{S_k}{MAX - ITERATION}\right)^{\gamma} \tag{4}$$

2.1.3. Defense strategy

In this strategy, the positions are updated on the army head, king as well as random soldier. The main goal of the defense strategy is for protecting the kings from battle. In the war, the army troops are utilized for investigating the larger area of the search spaces. The army changed its strategy dynamically from time to time for confusing the opposing army.

$$Z_k(v+1) = Z_k(v) + 2 \times \beta \times (\mathrm{K} - Z_{\Re and}(v)) + \Re and \times Y_k \times (e - Y_k(v)) \tag{5}$$

The war strategy explored more search spaces than the other strategies. The soldiers acquire larger steps and update their positions for larger values of Y_k.

2.1.4. Relocation/Replacement of weak soldiers

In this approach, various relocation schemes are tested. One of the simplest approaches is to replace weak soldiers with random soldiers. Then it is calculated and it is expressed as;

$$Z_x(v+1) = L_B + \Re and \times (U_B - L_B) \tag{6}$$

In the war field, the second technique is utilized for relocating the weak soldiers with the entire army. The convergence behaviors of the WSO algorithm are improved by this approach.

$$Z_x(v+1) = -(1 - \Re and) \times (Z_x(v) - MEDIAN(Z)) + \mathrm{K} \tag{7}$$

2.1.5. Exploitation and exploration

These are the two significant metaheuristic algorithms that determine a better trade-off strategy to enhance the approach effectively. The attack strategy indicates exploitation, as well as the defense strategy, is indicated by exploration. The essential factors of this approach are as follows;

- When a soldier moves to exploitation or exploration oriented by the rand variable.
- The q_s factor assisted the user to give flexibility for choosing the values based on a fitness function.

At the end of the war, the target areas are determined by using army troops as well as the army troops are surrounded by the target areas, then the commander and king are close to the target.

The WSO is a war strategy called Vyuha in which each kingdom is used to attack the opposing army and the only goal is to win the battle. The emperor and commanders in the army integrate the forces into specific units. Random attacks, signaling by drums, relocation of weak soldiers, defense strategy and traps by the opposition are some of the attacks that take part in war strategy. Every existing algorithm has its benefits well as drawbacks when it comes to achieving different objectives. For obtaining improved robustness and convergence, a different algorithm such as Genetic Algorithm (GA) (Katoch et al., 2021), Particle Swarm Optimization (PSO) (Samanta & Nataraj, 2009), Horse Herd Optimization (HHO) (Basu et al., 2023), and Grasshopper Optimization Algorithm (GOA) (Meraihi et al., 2021) has been used by different researchers. These algorithms are often improved using different strategies such as mutation, fuzzy logic, and quantum computing to improve their performance. But they suffer from different complexities such as slow convergence, constrained to local optima, and premature convergence. The PSO and GA algorithm has a slightly slower convergence rate and higher computational complexity when compared to the existing techniques.

The GOA algorithm often struggles to achieve an effective balance between the exploration and the exploitation phases. The HHO algorithm often suffers from premature convergence when applied to complex engineering problems such as signal processing and intelligent fault diagnosis. The increased number of algorithm-related parameters is another problem that improves the computational complexity. As per the No Free Lunch theorem, a single optimization algorithm cannot satisfy the objective functions of different engineering problems. The WSA algorithm offers improved performance and overcomes different drawbacks presented in the above section.

3. Proposed methodology

One of the important analytical solutions for predicting the failure of the equipment is survivability analysis, which monitors the performance of the input operational data. The need for numerous past historical data points has been identified to automate the prediction of failure equipment. This is not always possible, as the input data levels leading to the failure of that apparatus may be limited or absent from the input dataset. Some solutions based on deep learning (DL) methods are developed for asymmetric initial datasets. Although the models developed in such cases have been observed to suffer from the problem of bias because of their poor generalization. Our research aims to solve the problem by proposing a novel Sugeno Fuzzy Integral Convolutional based War Strategy Algorithm (SFEC-WSA) to understand the input data dynamics. The overall system design for the SFEC-WSA method is delineated in Fig. 1.

3.1. Survival analysis

Artificial intelligence (AI) plays a major role in automating applications as well as it makes human life easier. In the sector, monitoring the operational lifetime of the equipment or device is a significant core requirement and it has some implications to manage the operational costs effectively. The survival analysis is constructed through statistical approaches and utilized for predicting whether the event occurred or not in the given input feature or data.

Survival analyses are mainly utilized in industries for preventing failure in device equipment or machines. The dataset is created with input data for predicting whether the device is operating normally or not. The input characteristics of the device contain metrics like rotation, voltage, vibration, and pressure. According to the input characteristics, the failure or normal case is denoted in the binary target variable. Based on the input data metrics, the target classes are balanced for predicting the failure case automatically. The deep learning (DL) techniques work effectively in the balanced dataset when compared to other unbalanced datasets. The predictions of the fault scenario are complicated for determining the input data combination that leads to a failure case. A reliable and robust algorithm based on Sugeno Fuzzy Integral Convolutional based War Strategy Algorithm (SFEC-WSA) is proposed for solving this type of scenario.

3.2. Sugeno fuzzy integral ensemble (SFE)

Ensemble learning is the strategy utilized to fuse the key characteristics with two or more base learners. The ensemble minimized the variance by predicting the errors because the framework is more robust than other designs. The majority of the conventional ensemble approaches are used for assigning the pre-defined classifier weight for calculating the ensemble. The fuzzy integral-based method is utilized to assign the fixed weight for the classifier (Kundu et al., 2021). The

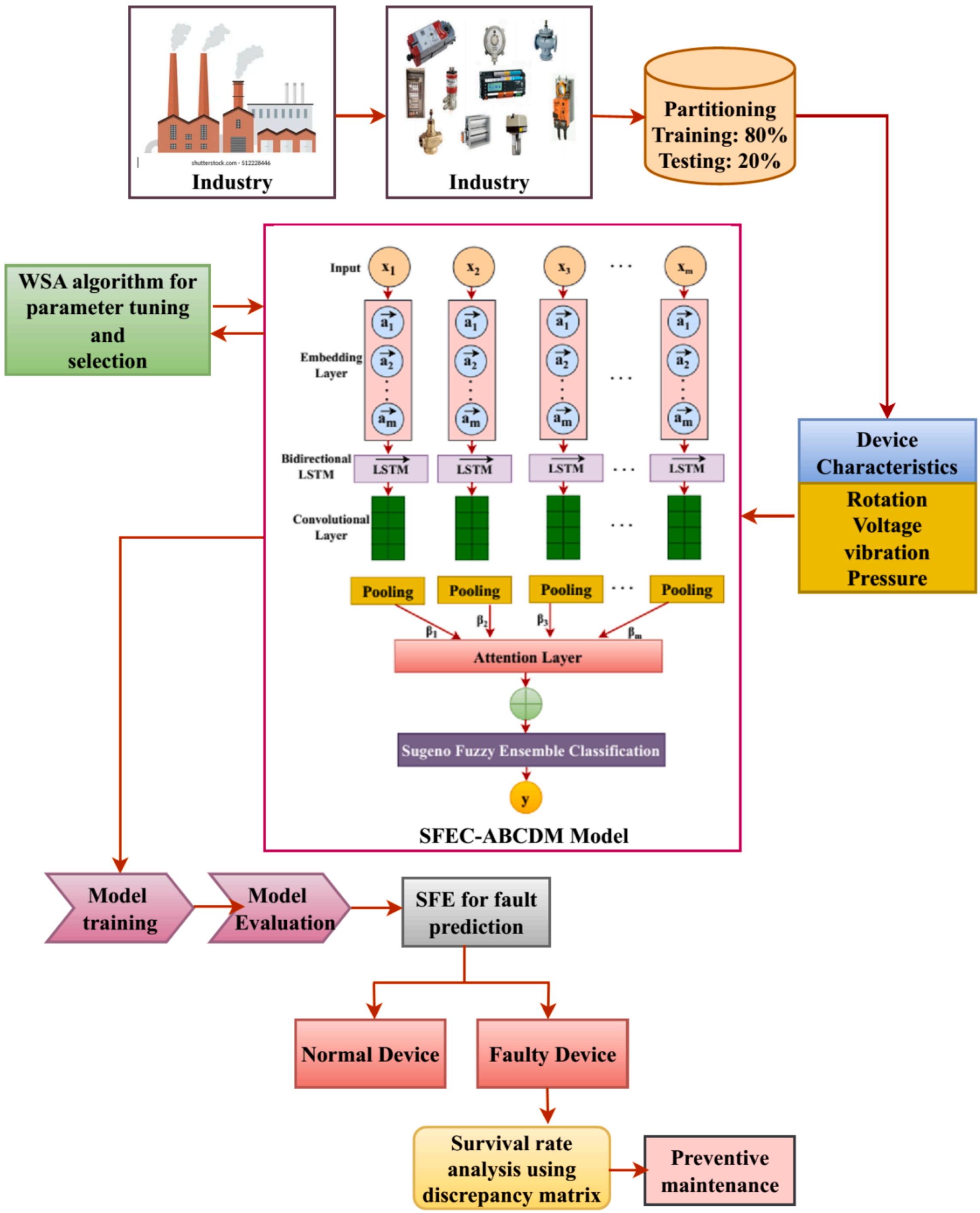

Fig. 1. System architecture design.

algorithm is more robust when compared to other conventional approaches. The fuzzy integrals proved that they successfully solved the various pattern recognition issues. They are flexible and powerful functions to aggregate information according to fuzzy measures. If the aggregation is calculated, the fuzzy measure indicates the importance or relevance of the sources of constituent information.

The fuzzy measure is considered as the set function g and it satisfies some properties are explained as follows;

$$g(\varphi) = 0\,, \quad g(Y) = 1$$

2. $B, C \in \gamma$ and $B \subseteq C$, implies $g(B) \leq g(C)$
3. If $D_o \in \gamma, D_1 \subseteq D_2 \subseteq D_3 \subseteq .... \subseteq D_o$ then $LIM_{o\to\infty} g(D_o) = g(LIM_{o\to\infty} D_o)$

From the above equation, the Borel field with an arbitrary set Y is represented by γ, the total number of information sources are represented by O. The Sugeno-β measure satisfies some conditions and they are followed as;

$$g_\beta(T) = 1$$

2 If $f_j \cap f_k = \varphi$, then ∃ b $\beta > -1$ then;

$$g_\beta(f_j \cup f_k) = g_\beta(f_j) + g_\beta(f_k) + \beta . g_\beta(f_j)(f_k) \tag{8}$$

From the above equation, the real root is represented by β.

$$\beta + 1 = \prod_{o=1}^{O} (\beta, g(f_o) + 1) \tag{9}$$

The Sugeno integral with the measurable function g for the fuzzy measure is computed and expressed in the below equation;

$$\int g(y) d\Omega = \underset{1 \le j \le o}{MAX} \left(MIN \left(g\left(y_j\right), \Omega\left(B_j\right) \right) \right) \tag{10}$$

From the above equation, the ranges are represented by $\Omega(B_j) = \Omega\left(\left\{y_j, y_{j+1}, y_{j+2}, \ldots\ldots, y_o\right\}\right)$ and $\{g(y_1), g(y_2), \ldots.., g(y_o)\}$ as well as it is defined as $g(y_1) \le g(y_2) \le g(y_3) \le \ldots.. \le g(y_o)$. The pseudo-code of Sugeno Fuzzy Integral Ensemble is expressed in algorithm 1.

Algorithm 1: Pseudo code of Sugeno Fuzzy Integral Ensemble

Step 1: Input initialization
Probability score (Q), the total number of base learners (*NUM_LEARNERS*), fuzzy measures ($\mathfrak{I}$), and the number of dataset classes (*NUM_CLASSES*).
Step 2: Output
Prediction of final class ($\hat{x}$).
Step 3: Initialize, β by using equation (2) and predictions from the empty list.
Step 4: **for** the class index (j) $\in \{0, 1, 2, \ldots, NUM\_CLASSES - 1\}$ **do**
Array Q sorted in descending order,
Permutation of $\mathfrak{I}$,
$g(f)_{pre} \leftarrow \mathfrak{I}_{\pi[0]}$,
$Fuzzy\_Prediction \leftarrow MIN(Q_{\pi}[0], \mathfrak{I}_{\pi}[0])$
for $o \in \{0, 1, 2, \ldots., NUM\_LEARNERS\}$ **do**
$g(f)_{curr} \leftarrow g(f)_{pre} + \mathfrak{I}_{\pi}[o] + \beta \cdot \mathfrak{I}_{\pi}[o] \times g(f)_{pre}$,
$Fuzzy\_Prediction \leftarrow MAX(Fuzzy\_Prediction)$,
$MIN(Q_{\pi}[o], g(f)_{curr}))$,
$g(f)_{pre} \leftarrow g(f)_{curr}$.
end for
$Prediction[j] \leftarrow Fuzzy\_Prediction$
end for
Step 5: $\hat{x} \leftarrow ArgMAX(Prediction[j])$.

3.3. Attention-based Bidirectional CNN-RNN deep model (ABCDM)

The DL designs are considered as ABCDM which limited the existing deep architectures for both long and short users to detect the popularity in sentiment analysis (Basiri et al., 2021). The long-term dependencies and local features were captured by using CNN, bidirectional LSTM, attention mechanism, GloVe word embedding, and bidirectional GRU. The GloVe word embedding matrices are generated $G_w \in Q^{m \times b}$ with b and m being the embedding dimension and the total number of words is utilized for enabling the comment vector with n being the padding length or the maximum number of words $q_e, e \in [1, n]$ is followed as;

$$v_e = G_w q_e, e \in [1, n] \tag{11}$$

The embedding layer output is arranged in the form of backward and forward arbitrary length and exact long dependence which applies to two parallel layers Bi-GRU and Bi-LSTM. The LSTM and GRU are enabled by both long and shortest order.

$$\overrightarrow{a}_{e_{LSTM}} = \overline{LSTM}(v_e), e \in [1, n] \tag{12}$$

$$\overrightarrow{a}_{e_{LSTM}} = \overline{LSTM}(v_e), e \in [n, 1] \tag{13}$$

$$\overrightarrow{a}_{e_{GRU}} = \overline{GRU}(v_e), e \in [1, n] \tag{14}$$

$$\overrightarrow{a}_{e_{GRU}} = \overline{GRU}(v_e), e \in [n, 1] \tag{15}$$

We can able to get the forward and backward context using $q_{e\ a}$ word for each concatenating as follows:

$$a_{e_{LSTM}} == \left[\overrightarrow{a}_{e_{LSTM}}, \overleftarrow{a}_{e_{LSTM}}\right] \tag{16}$$

$$a_{e_{GRU}} == \left[\overrightarrow{a}_{e_{GRU}}, \overleftarrow{a}_{e_{GRU}}\right] \tag{17}$$

The term $a_{e_{LSTM}}$ and $a_{e_{GRU}}$ the word focus mechanism are used and can make the model in high or less attention. The different modified word comments are as follows:

$$c_{e_{LSTM}} = ebma\left(G_{q_{LSTM}} a_{e_{LSTM}} + d_{q_{LSTM}}\right) \tag{18}$$

$$c_{e_{GRU}} = ebma\left(G_{q_{GRU}} a_{e_{GRU}} + d_{q_{GRU}}\right) \tag{19}$$

$$\beta_{e_{LSTM}} = \frac{\exp\left(c^{e}_{e_{LSTM}} c_{e_{LSTM}}\right)}{\sum_e \exp\left(c^{e}_{e_{LSTM}} c_{e_{LSTM}}\right)} \tag{20}$$

$$\beta_{e_{GRU}} = \frac{\exp\left(c^{e}_{e_{GRU}} c_{e_{GRU}}\right)}{\sum_e \exp\left(c^{e}_{e_{GRU}} c_{e_{GRU}}\right)} \tag{21}$$

$$R_{LSTM} = \sum_e \alpha_{e_{LSTM}} a_{e_{LSTM}} \tag{22}$$

$$R_{GRU} = \sum_e \alpha_{e_{GRU}} a_{e_{GRU}} \tag{23}$$

where c_q is the vector of context which may be used to learn jointly on the training and initialize randomly. The term c_e is hidden represented a_e and also the term c_q and c_e is derived as a similarity of the important word. When the important weights α_e are applied to the weighted sum and it changes the term R. The term R is the vector of comment which is used to shorten the all information in the comment.

The convolution operation is utilized for the extraction of local features and reduces input data dimensionality after acquiring the final comment representation R. The convolution allows the model to obtain position constancy. For Bi-LSTM and Bi-GRU branches, two convolutional layers with the variant kernel are applied individually in ABCDM. The integration of 1D-CNN along with diverse window sizes and a lot of constant filters are employed for Bi-GRU and Bi-LSTM output individually.

The two individual CNNs are employed for the Bi-GRU and Bi-LSTM layers output because of the presence of CNN layers' 4 output. On the CNN layer's output, the average and maximum pooling layers are piled up individually for feature-down sampling. Then the feature maps become more powerful for the feature's position change. In the CNN layer, the number of filters d is considered and then every pooling operation's final feature vector is expressed in the below equation.

$$Mv_j = [mv_1, mv_2, \ldots\ldots, mv], j \in [1, 8] \tag{24}$$

The numerical expression of the output layer is expressed in the below equation. The 8 feature vectors are coupled for the final vector formation and are expressed in the below equation.

$$Mv = [Mv_1, Mv_2, \ldots..Mv_8] \tag{25}$$

To accelerate overfitting and network training, batch normalization is applied and acquire the vector Mv. The fully coupled dense layer is used for the prediction of the comment's sentiment polarity to change Mv the vector into the representation of high-level sentiment. The numerical expression of the output layer is given below.

$$a_f = \mathrm{Re}lu\left(G_b a_s + d_f\right) \tag{26}$$

From the above equation, a_s represents hidden representation, G_b and d_f represents parameters acquired in the training process. At last, the output of the dense layer is generated through the sigmoidal function in favor of binary categorization. The architecture of the ABCDM method is given below (Fig. 2),

The fault detection of the device is determined by integrating the attention layer with CNN. This is performed with large data sets and the failure of the device is predicted from input data. In this combination, the merging of the attention layer generates the Sugeno fuzzy classification output for identifying the survival analysis of the input node. We

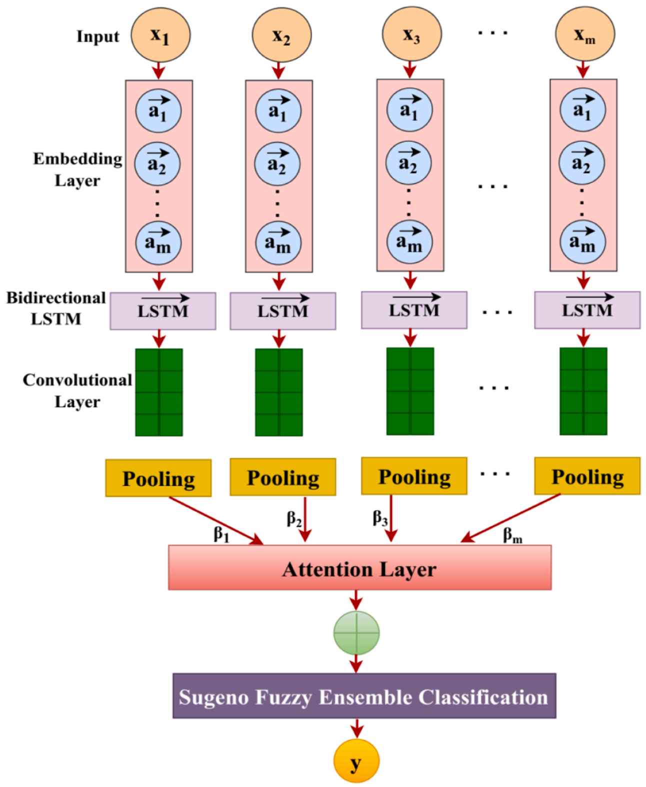

Fig. 2. Architecture of ABCDM.

individually employed two parallel convolutional layers for the BiGRU and BiLSTM classifiers. Hence, four outputs are derived from the individual CNN classifiers which serve as the inputs to the Sugeno fuzzy ensemble classifier. Using the classification combination approach, the Sugeno fuzzy ensemble classifier identifies the different outcomes, and the fuzzy confidence score is acquired using the Sugeno interval. For the different CNN classifier combinations, the remaining fuzzy measure value is computed after identifying the Sugeno fuzzy measure. The fuzzy measure values are optimally set using the WSA algorithm during training to overcome the parameters set by trial and error and manual tuning.

3.4. Sugeno fuzzy ensemble Convolutional-based war strategy algorithm (SFEC-WSA) for survival analysis

Fig. 3 describes the working procedure of the proposed Sugeno Fuzzy Ensemble Convolutional-based War Strategy Algorithm (SFEC-WSA) for identifying the survival time of devices. The proposed SFEC system integrates the process of both the Sugeno fuzzy integral ensemble model and the Attention-based Bidirectional CNN-RNN Deep Model (ABCDM). Moreover, to enhance the performance of prediction results, the parameters SFEC model is reweighted adaptively using the war strategy algorithm. The proposed SFEC-WSA analyses several parameters such as vibration, rotation, voltage, and pressure to evaluate the condition of the equipment.

Initially, the Parameters of ABCDM, total base learners, and data classes are initialized. From the inputted data, the significant data from the information source are measured using fuzzy metrics. In addition, to improve the training performance and minimize overfitting issues, the batch normalization layer of the ABCDM concept is infused with it. The learning parameters of the SFEC model are optimized using the war strategy algorithm (WSA) to enhance the prediction efficiency. Thus, the proposed SFEC-WSA approach accurately predicts the device survival time.

Assume an identical device N generated by the linked systems a_d

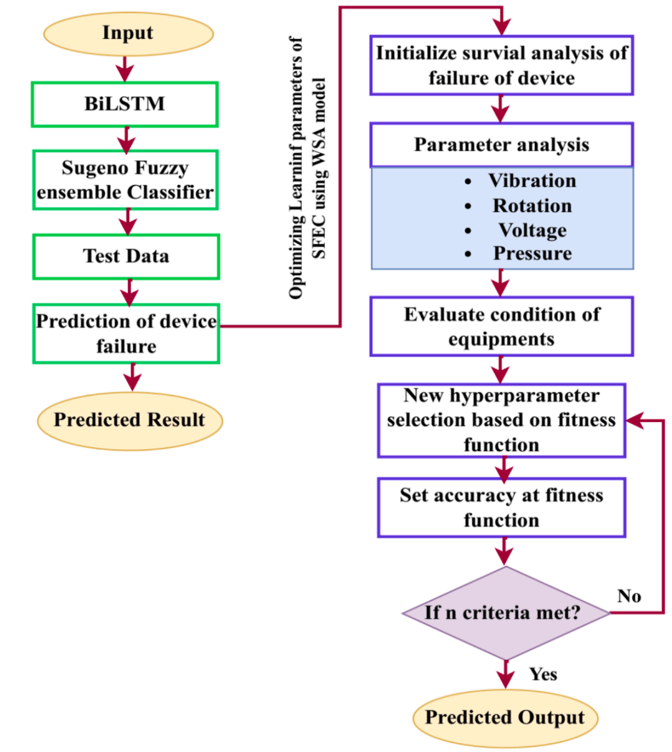

Fig. 3. Flow diagram of SFEC-WSA.

with the survival analysis time $S \in \Re^{+}$. The identification of device failure affects the overall process and generates an abnormal system operation. The working of the device is monitored by various sensors u_s, and the failure of the system determines v_s as well as the data collected from the input is stored as ℓ . The survival analysis device represented as S_g^n in which $n = 1, \cdots, N$ that halted the working condition of the device.

The objective of the research is to predict the failure of the device from the input data and analyze the survival time from large datasets. These are to be detected based on the evaluation of the lifetime of the device, failure, and survival analysis data which helps to monitor the device to enhance its performance. To achieve the goal the SFEC-WSA algorithm is proposed to predict the robustness based on the input data with varied features.

The expression for the device component is formulated as

$$v = \left(v_1, v_2, \cdots, v_{a_d}\right) \in \{0, 1\}^{a_d} \tag{27}$$

The device function is determined when y_j the value becomes one other it tends to be zero. The state space of the device monitors all the possible functions of v in which the structured data is determined by $\varphi : \{0,1\}^{a_d} \rightarrow \{0,1\}$. However, if the device function attains $\varphi(v) = 1$ then it terminates the functioning of the device, or if it achieved the functional value of 0 the working condition is performed in a better way. The structured data functions based on parallel and series systems are expressed as

$$\varphi(v) = \bigwedge_{j=1}^{a_d} v_j \tag{28}$$

$$\varphi(v) = \bigvee_{j=1}^{a_d} v_j \tag{29}$$

where the logic AND and OR operator is indicated as $\wedge$ and $\vee$. The functioning of the device is not performed best when failure is detected. So if a device fails then it damages all the component analysis otherwise the functioning is performed properly.

The survival analysis time of the device is monitored by $h = 1, \cdots, H$

sensors. The evaluation of monitoring the device is formulated as

$$\ell = \left\{ \left\{ U_s^n , v_s^n \right\}_{s=0}^{S_{LIFE}^n} \right\}_{n=1}^{N} \tag{30}$$

From the above equation, the state vector of the device is denoted as v_s^n and ℓ denotes the data set. The expression of the data matrix is written as

$$U_s^n = \begin{pmatrix} u_{s,1}^n \\ u_{s,2}^n \\ \vdots \\ u_{s,a_d}^n \end{pmatrix} = \begin{pmatrix} u_{s,1,1}^n & u_{s,1,2}^n & \cdots & u_{s,1,H}^n \\ u_{s,2,1}^n & u_{s,2,2}^n & \cdots & u_{s,2,H}^n \\ \vdots & \vdots & \ddots & \vdots \\ u_{s,a_d,1}^n & u_{s,a_d,2} & \cdots & u_{s,a_d,H}^n \end{pmatrix} \in \Re^{a_d \times H} \tag{31}$$

The device measurement vector is indicated by $u_{s,i,h}^n \in \Re^H$. The data structure is highly applicable in the field of engineering applications for monitoring the performance of the device continuously based on input features. The fitness of the WSA algorithm is the loss rate of the Sugeno fuzzy ensemble model which is the error value computed between the actual and predicted output.

$$F(X) = \rho - \widehat{\rho} \tag{32}$$

F(X) is the fitness function that is used to compute the error value of the Sugeno fuzzy ensemble model and ρ is the predicted output whereas $\widehat{\rho}$ is the actual output. The F(X) is an error function that analyzes the internal parameters (weights and biases) of the Sugeno fuzzy ensemble classifier. The WSA optimizer minimizes this error rate to improve the prediction accuracy of the classifier. If an error occurs then it is propagated back to the previous layer and then the weights and biases of these layers are modified to minimize the error rate.

3.4.1. Fault detection

The detection of fault determined in the device is predicted based on the SFE classifier to incorporate the base learners. The data samples of the fault occurred devices are evaluated based on the fuzzy integral method to estimate the fixed weight of the classifier. The fault-detected devices are determined in the fuzzy integral to solving different recognition issues. Fig. 4 depicts the prediction of device failure based on the SFE classifier.

4. Results and discussions

The proposed Sugeno Fuzzy Ensemble Convolutional based War Strategy Algorithm (SFEC-WSA) approach is employed to analyze the survival time of devices. To obtain the survival time, various tests are conducted and that is clearly explained in the below subsections.

4.1. Experimental setup

The performance analysis of the SFEC-WSA technique is implemented in an Intel i5 processor along with 16 GB RAM.

4.2. Dataset description

The unbalanced dataset is used to analyze the survival time of structured data with the help of some parameters such as vibration, rotation, voltage, and pressure. The ON and OFF condition of the device is predicted by using these parameters. The predictive maintenance problem affects the dataset from unbalanced classes so three types of device data are utilized. The first device data is denoted as Device-1that has 8761 data separated into 44 failed classes and 8717 normal classes. The second device data is represented as Device-2 which has 8761 data divided into 41 failed classes and 8720 normal classes. The third device data is depicted as Device-3 which has 8761 data split into 40 failed classes and 8721 normal classes. In general, the data sizes used for training and testing processes are 80% and 20% respectively.

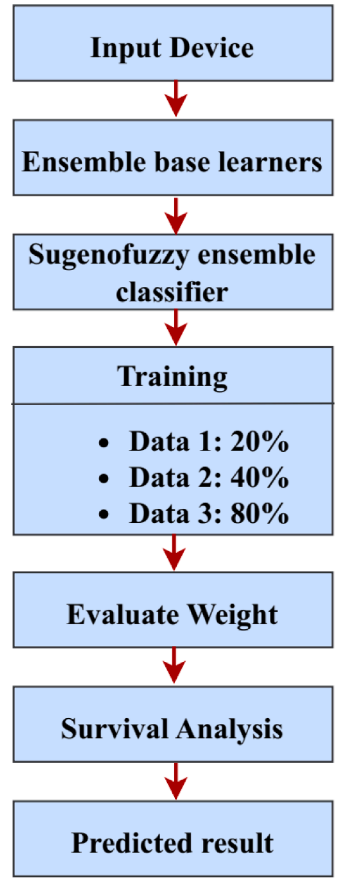

Fig. 4. Fault identification of the device based on SFE classifier.

4.3. Hyperparameter configuration

The hyperparameter tuning is performed to predict the optimal hyperparameter values which enhance the performance of the proposed SFEC-WSA approach. The hyperparameter configuration of the proposed SFEC-WSA approach is explained in Table 1.

Table 1
Hyperparameter configuration.

Techniques	Parameters	Ranges
WSO	Population size	30
	Maximum number of optimization	1000
	Soldier size	30
	Number of unimodal functions	25
	Number of multimodal functions	25
Ensemble Sugeno Fuzzy Integral	Total number of epochs	100
	Loss function	Cross entropy
	Momentum	0.99
	Batch size	16
	Optimizer	Stochastic Gradient Descent
	Initial learning rate	0.0001
	Learning rate decay period	10 epochs
ABCDM	Decay rate	10^{-10}
	Dropout rate	0.2
	Learning rate	10^{-3}
	Batch size	512
	Optimizer	Adam Stochastic optimizer
	Loss function	Binary cross entropy
	Padding size	45

4.4. Evaluation metrics

For achieving the better performance rate of the proposed SFEC-WSA approach, a few performance evaluation metrics such as precision (P), accuracy (A), F1-score ($\mathfrak{I}$), and recall ($\mathfrak{R}$) are utilized.

Accuracy (A):

Accuracy is the closeness measurement to reach an actual value that is expressed as,

$$A = \frac{predicted\ value - actual\ value}{actual\ value} \tag{32}$$

Precision (P):

Precision is defined as a closeness measurement between two or more measurements that are formulated as,

$$P = \frac{correctly\ predicted\ positive\ values}{correctly\ and\ incorrectly\ predicted\ positive\ values} \tag{33}$$

Recall ($\mathfrak{R}$):

The recall can determine all relevant cases in the model within the specific dataset is formulated as,

$$\mathfrak{R} = \frac{correctly\ predicted\ positive\ values}{all\ predicted\ values} \tag{34}$$

F1-score ($\mathfrak{I}$):

The harmonic mean of recall and precision is known as F1-score and is also used to evaluate the binary classification systems. The F1-score is derived by,

$$\mathfrak{I} = 2^* \frac{\mathfrak{R}^* P}{\mathfrak{R} + P} \tag{35}$$

4.5. Performance analysis

To analyze the performance of the proposed SFEC-WSA approach, some parameters such as vibration, rotation, voltage, and pressure are used for analyzing the input data features of Device-1, Device-2, and Device-3. The input data feature values for training data are described in Table 2and the input data feature values for testing data are explained in Table 3. From this table 2 and 3, the minimum range of training data is higher compared to the minimum range of testing data. But the maximum range of testing data is higher than the maximum range of training data.

The 20%, 40%, and 80% of training data sizes are included to determine the performance of the proposed SFEC-WSA approach and the performance analysis is conducted based on the performance evaluation metrics such as accuracy, precision, recall, and F1-score. Fig. 5(a-c) represents the performance rate of various performance metrics namely recall, accuracy, F1-score, and precision. This performance rate evaluation is conducted for 20%, 40%, and 80% of training data. The performance rate of 20% is lower compared to the remaining 40% and 80% of training data.

In 20% of training data, the performance rate of 68.5%, 69.7%, 66.23%, and 67.90% are attained from accuracy, precision, recall, and F1-score respectively. The metrics such as accuracy, precision, recall, and F1-score provide the performance rate of 85.4%, 86.7%, 83.52%, and 84.81% respectively which are captured from 40% of training data. From this analysis, superior performance is obtained from 80% of training data.

4.6. Comparative analysis

For comparative analysis, the proposed SFEC-WSA approach validates the performance by comparing with the existing methods such as Reinforcement Learning based Double Deep Q Network (RL-DDQN), Deep Piecewise Exponential Additive Mixed Model (DeepPAMM), Semi-Supervised Multi-Task learning (SSMTL) and Shapley Additive exPlanations (SHAP) algorithm.

Fig. 6 shows the performance analysis of various metrics for 20% of training data. The comparison is performed by using various methods namely RL-DDQN, DeepPAMM, SSMTL, SHAP, and the proposed SFEC-WSA approach. The proposed SFEC-WSA approach has a higher performance rate compared to other conventional methods. In 20% of training data, the performance rate of 68.5%, 69.7%, 66.23%, and 67.90% are attained from accuracy, precision, recall, and F1-score respectively.

Fig. 7 portrays a performance analysis using various performance analysis metrics namely precision, accuracy, F1-score, and recall for 40% of training data. Each performance metric is compared by different approaches such as RL-DDQN, DeepPAMM, SSMTL, SHAP, and the proposed SFEC-WSA approach. Among all those analyses, the proposed SFEC-WSA approach achieved a high performance rate. The metrics such as precision, accuracy, F1-score, and recall provide the performance rate of 85.4%, 86.7%, 83.52%, and 84.81% respectively which are captured from 40% of training data.

The performance analysis is evaluated for 80% of training data is depicted in Fig. 8. The approaches namely RL-DDQN, DeepPAMM, SSMTL, SHAP, and the proposed SFEC-WSA approach are employed for predicting the performance rate. This comparative analysis showed that the proposed SFEC-WSA approach achieved a higher performance rate. The superior performance is obtained from the 80% of training data.

Table 4 depicts the comparative analysis of different metrics. The comparison with various parameters is performed in the proposed and existing methods by the training data 20%, 40%, and 80%. The 20% and 40% training data performance is slightly diminished and the 80% training data attained a superior performance by achieving an accuracy of 97.2%.

Comparative analysis for Device-1:

Execution time is the time taken to complete the task and the comparative analysis of execution time is depicted in Fig. 9. The comparative analysis required some approaches such as RL-DDQN, DeepPAMM, SSMTL, SHAP, and the proposed SFEC-WSA approach to determine the performance superiority. The proposed SFEC-WSA approach got a better execution time of 0.44 s compared to other existing methods.

Comparative analysis for Device-2:

Fig. 10 presents the execution time of different methods such as RL-DDQN, DeepPAMM, SSMTL, SHAP, and the proposed SFEC-WSA approach. The proposed SFEC-WSA approach has a low execution time of 0.3 s and the SSMTL method attained a higher execution time of 0.86 s. The remaining approaches like RL-DDQN, DeepPAMM, and SHAP have an execution time of 0.56 s, 0.75 s, and 0.66 s respectively. This analysis indicates the superior performance of the proposed SFEC-WSA approach.

Table 2
Input data feature values for training data.

Input data features	Device-1		Device-2		Device-3	
	Minimum range	Maximum range	Minimum range	Maximum range	Minimum range	Maximum range
Vibration	22.7835	68.4683	23.4792	67.4260	24.4793	65.3893
Volt	119.3479	227.4893	99.3792	236.4793	118.9086	225.6858
Pressure	68.3720	143.3678	70.4738	143.4904	59.4793	144.1294
Rotate	248.3792	600.3791	186.4839	633.4784	243.4894	631.4703

Table 3
Input data feature values for testing data.

Input data features	Device-1		Device-2		Device-3	
	Minimum range	Maximum range	Minimum range	Maximum range	Minimum range	Maximum range
Vibration	21.4793	68.4784	18.4748	72.4783	19.4793	66.4839
Volt	117.4760	239.5791	109.3290	242.6419	112.7590	234.5672
Pressure	56.3021	143.9503	62.4803	154.3792	62.4829	150.4783
Rotate	213.2895	638.4893	181.4783	640.3879	234.4783	636.5784

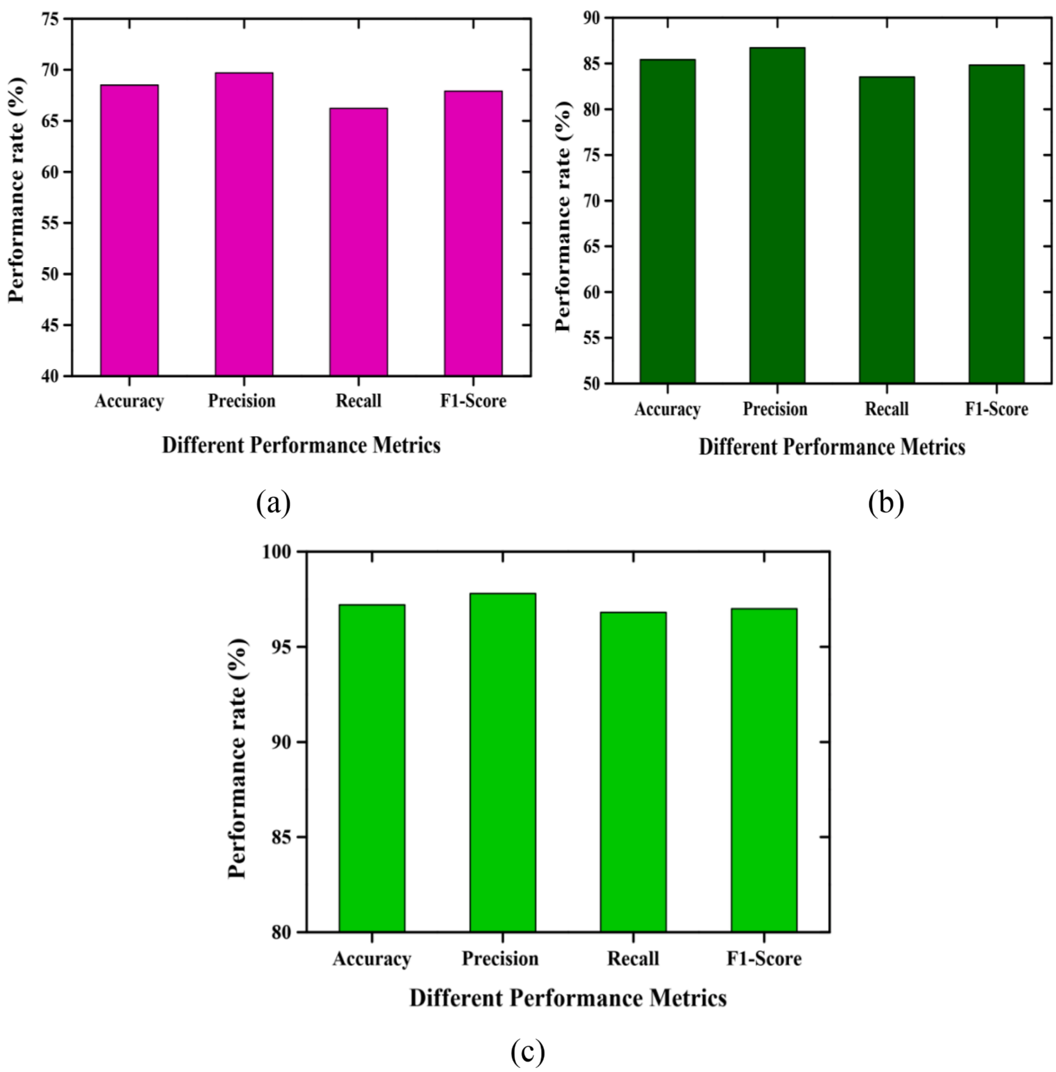

Fig. 5. Performance evaluation of proposed SFEC-WSA approach using (a) 20% of training data (b) 40% of training data (c) 80% of training data.

Comparative analysis for Device-3:

Fig. 11 shows the execution time of various methods namely RL-DDQN, DeepPAMM, SSMTL, SHAP, and the proposed SFEC-WSA approach. The proposed SFEC-WSA approach attained a higher performance when compared to other conventional methods. The execution time of 0.73 s, 0.64 s, 0.85 s, 0.575 s, and 0.33 s are attained from RL-DDQN, DeepPAMM, SSMTL, SHAP, and the proposed SFEC-WSA approach respectively.

Fig. 12 depicts the box plot graph for the proposed method. The 80% training data is determined to validate the accuracy performance. The box plot graph is used to demonstrate the way of distributing the data from a group to estimate the survival analysis by predicting a large data set.

The convergence rate of the WSA algorithm is compared to different algorithms such as GA (Katoch et al. 2021), PSO (Samanta & Nataraj, 2009), HHO (Basu et al.2023), and GOA (Meraihi et al.2021), and the results are presented in Fig. 13. The experiment is conducted for a total of 30 iterations. The results show that the convergence rate of the WSA algorithm is superior to the HHO, GOA, GA, and PSO algorithms. The existing techniques often suffer from premature convergence, local optimal trapping, and higher computational complexity when applied to the machine survival rate analysis domain.

5. Conclusion

The heart of the manufacturing industry is the rotating machines and improving the survival rate of these machines is one of the important priorities of the maintenance engineers. To ensure a proper maintenance

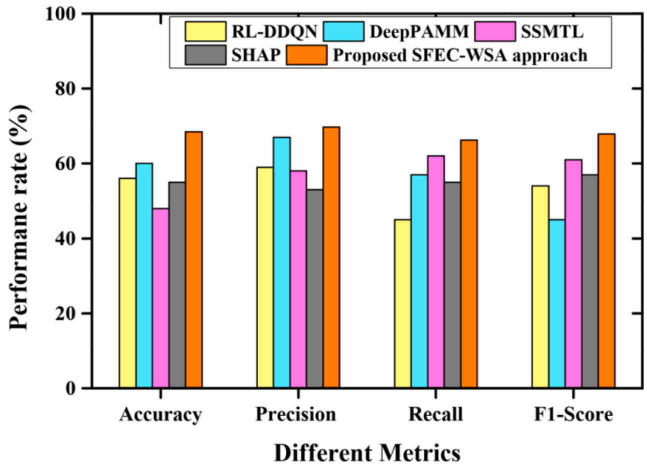

Fig. 6. Performance analysis based on training data for 20%.

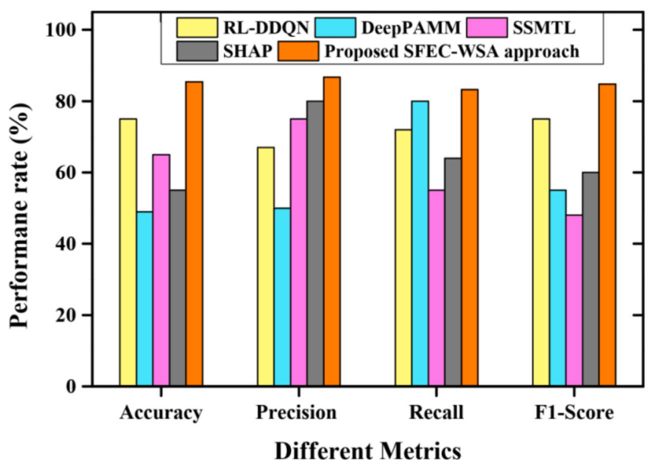

Fig. 7. Performance analysis for 40% of training data.

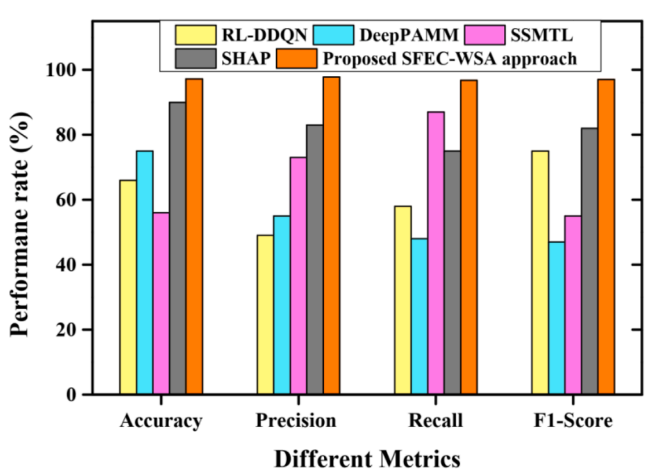

Fig. 8. Performance analysis for 80% of training data.

strategy. Here, the serves as an intelligent predictive model that can evaluate the survival rate of the machinery and determine the type of fault. Here different deep learning and machine learning techniques are used to achieve this objective. This work mainly aims to improve the accuracy and reliability of survival node analysis via a novel technique to minimize the high complexity of the machines. The survival analysis is determined to identify the failure of the device from the

Table 4
Comparison of the proposed method with different parameters.

Metrics	Training data	RL-DDQN	Deep PAMM	SSMTL	SHAP	Proposed SFEC-WSA
Accuracy	20%	57.2	60	46.5	53.8	68.5
	40%	77.2	44.8	60.3	53.2	85.4
	80%	64.1	73.8	57.5	86.9	97.2
Precision	20%	56.4	63.8	55.9	50.2	69.7
	40%	62.3	44.6	73.6	79.5	86.7
	80%	43.2	46.8	70.8	80.1	97.8
Recall	20%	42.3	56.7	60.2	51.8	66.23
	40%	75.2	79.1	53.6	62.1	83.52
	80%	57.4	44.8	85.3	76.4	96.8
F1-score	20%	56.9	41.3	60.1	52.4	67.90
	40%	75.3	53.5	45.3	56.1	84.81
	80%	74.1	43.8	51.2	78.2	97

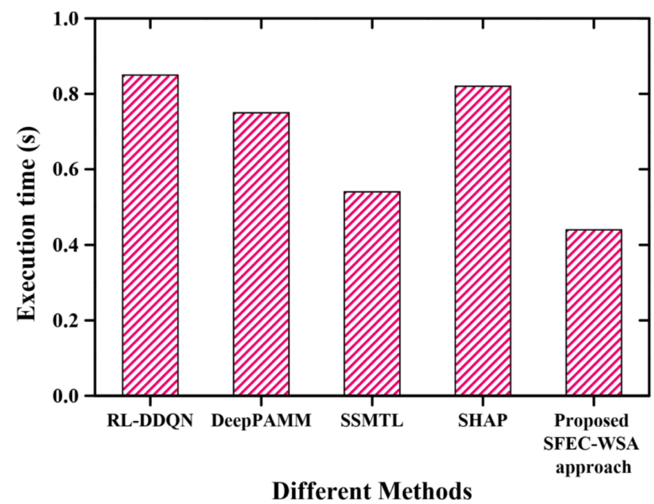

Fig. 9. Execution time analysis for Device-1.

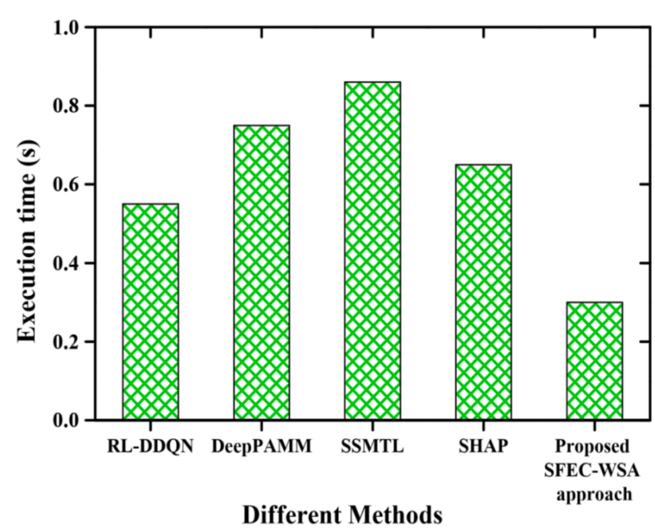

Fig. 10. Execution time analysis for Device-2.

manufacturing sector. The existing RL-DDQN, DeepPAMM, SSMTL, and SHAP methods are obtained to detect device failure with large data. But it could not process the analysis with high dimensional data and could not able to detect the failure of the device with input data. So in order to overcome the issue in this paper, the SFEC-WSA approach is proposed for analyzing the survival time of devices and minimizing their failure probability. The unbalanced dataset is used to analyze the survival time

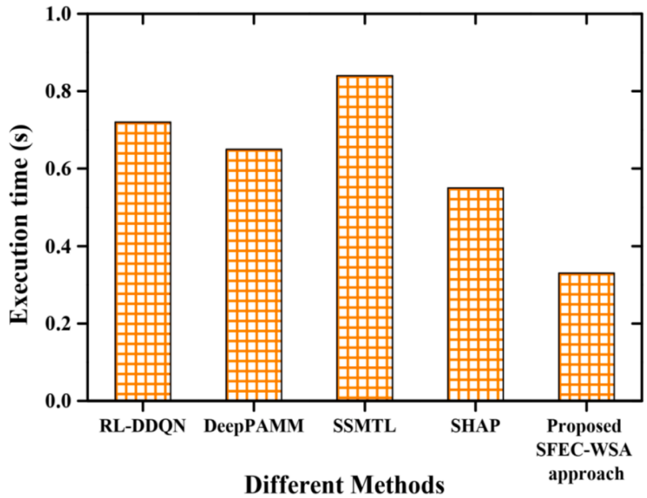

Fig. 11. Execution time analysis for Device-3.

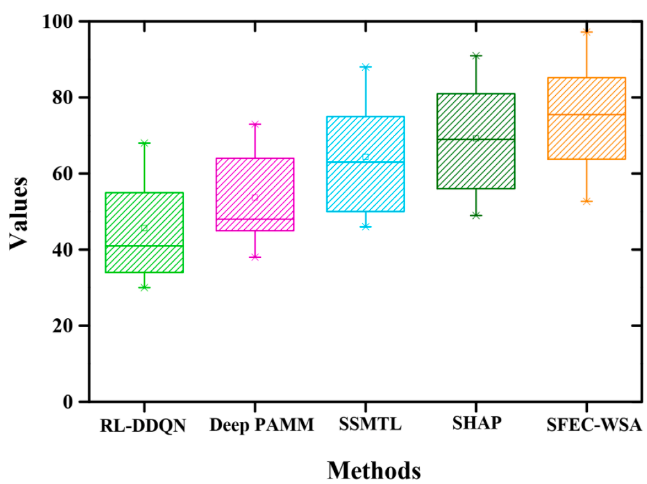

Fig. 12. Box plot graph.

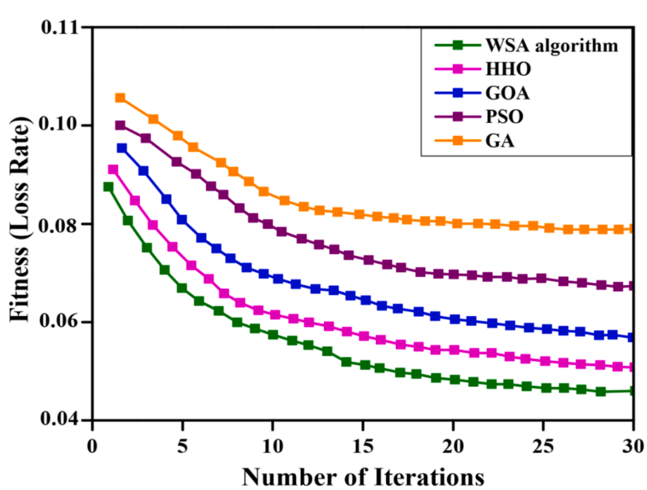

Fig. 13. Convergence rate comparison of different metaheuristic algorithms.

of structured data with the help of some parameters such as vibration, rotation, voltage, and pressure. The predictive maintenance problem affects the dataset from unbalanced classes so three types of device data such as Device-1, Device-2, and Device-3 are utilized. For achieving the better performance rate of the proposed SFEC-WSA approach, a few performance evaluation parameters like precision, accuracy, execution time, recall, and F1-score are utilized. The 20%, 40%, and 80% of training data sizes are included to determine the performance of the proposed SFEC-WSA approach. The performance rate of 20% is lower compared to the remaining 40% and 80% of training data. The performance of the proposed method is enhanced by attaining the accuracy, precision, recall, and F1-score of 97.2%, 97.8%, 96.8%, and 97% respectively for 80% of training data. The proposed SFEC-WSA approach achieved an execution time of 0.44 s, 0.3 s, and 0.33 s that are obtained from Device-1, Device-2, and Device-3 respectively. The experimental result showed that the proposed SFEC-WSA method attained superior performance than other conventional methods. In the future, the proposed method is applied to the real-world dataset for further enhancement of the system.

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Informed Consent

For this type of study informed consent is not required.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and material

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Code availability

Not applicable.

Author contributions

SS agreed on the content of the study. SS, EG, ASS and GR collected all the data for analysis. SS agreed on the methodology. SS, EG, ASS and GR completed the analysis based on agreed steps. Results and conclusions are discussed and written together. Both author read and approved the final manuscript.

CRediT authorship contribution statement

Soundararajan Sankaranarayanan: Conceptualization, Methodology, Software. **Elangovan Gunasekaran:** Data curation, Writing – original draft. **Amir shaikh:** Visualization, Investigation, Supervision. **Govinda Rao S:** Software, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Almazroi, A. A. (2022). Survival prediction among heart patients using machine learning techniques. *Mathematical Biosciences and Engineering, 19*(1), 134–145.

Asutkar, S., Chalke, C., Shivgan, K., & Tallur, S. (2023). TinyML-enabled edge implementation of transfer learning framework for domain generalization in machine fault diagnosis. *Expert Systems with Applications, 213*, Article 119016.

Ayyarao, T. S., RamaKrishna, N. S. S., Elavarasan, R. M., Polumahanthi, N., Rambabu, M., Saini, G., … Alatas, B. (2022). War strategy optimization algorithm: A new effective metaheuristic algorithm for global optimization. *IEEE Access, 10*, 25073–25105.

Basiri, M. E., Nemati, S., Abdar, M., Cambria, E., & Acharya, U. R. (2021). ABCDM: An attention-based bidirectional CNN-RNN deep model for sentiment analysis. *Future Generation Computer Systems, 115*, 279–294.

Basu, S., Kumar, S., & Basu, M. (2023). Horse herd optimization algorithm for economic dispatch problems. *Engineering Optimization, 55*(5), 806–822.

Cabrita, R., Lauss, M., Sanna, A., Donia, M., Skaarup Larsen, M., Mitra, S., … van Schoiack, A. (2020). Tertiary lymphoid structures improve immunotherapy and survival in melanoma. *Nature, 577*(7791), 561–565.

Chi, S., Tian, Y., Wang, F., Wang, Y., Chen, M., & Li, J. (2021). Deep semisupervised multitask learning model and its interpretability for survival analysis. *IEEE Journal of Biomedical and Health Informatics, 25*(8), 3185–3196.

Coens, C., Pe, M., Dueck, A. C., Sloan, J., Basch, E., Calvert, M., … Devlin, N. (2020). International standards for the analysis of quality-of-life and patient-reported outcome endpoints in cancer randomised controlled trials: Recommendations of the SISAQOL Consortium. *The Lancet Oncology, 21*(2), e83–e96.

Deepa, P., & Gunavathi, C. (2022). A systematic review on machine learning and deep learning techniques in cancer survival prediction. *Progress in Biophysics and Molecular Biology*.

Dey, S., Bhattacharya, R., Malakar, S., Schwenker, F., & Sarkar, R. (2022). CovidConvLSTM: A fuzzy ensemble model for COVID-19 detection from chest X-rays. *Expert Systems with Applications, 206*, Article 117812.

Dhiravidachelvi, E., Senthil Pandi, S., Prabavathi, R., & Bala Subramanian, C. (2023). Artificial Humming Bird Optimization-Based Hybrid CNN-RNN for Accurate Exudate Classification from Fundus Images. *Journal of Digital Imaging, 36*, 59–72. https://doi.org/10.1007/s10278-022-00707-7

Ganggayah, M. D., Taib, N. A., Har, Y. C., Lio, P., & Dhillon, S. K. (2019). Predicting factors for survival of breast cancer patients using machine learning techniques. *BMC Medical Informatics and Decision Making, 19*(1), 1–17.

Hao, J., Kosaraju, S. C., Tsaku, N. Z., Song, D. H. & Kang, M. (2019). PAGE-Net: interpretable and integrative deep learning for survival analysis using histopathological images and genomic data. In *Pacific Symposium on Biocomputing 2020* (pp. 355-366).

Huang, Z., Zhan, X., Xiang, S., Johnson, T. S., Helm, B., Yu, C. Y., … Huang, K. (2019). SALMON: Survival analysis learning with multi-omics neural networks on breast cancer. *Frontiers in Genetics, 10*, 166.

Javaudin, F., Lascarrou, J. B., Le Bastard, Q., Bourry, Q., Latour, C., De Carvalho, H., … Leclere, B. (2019). Thrombolysis during resuscitation for out-of-hospital cardiac arrest caused by pulmonary embolism increases 30-day survival: Findings from the French National Cardiac Arrest Registry. *Chest, 156*(6), 1167–1175.

Kalpana, B., Reshmy, A. K., Senthil Pandi, S., & Dhanasekaran, S. (2023). OESV-KRF: Optimal ensemble support vector kernel random forest based early detection and classification of skin diseases. *Biomedical Signal Processing and Control, 85*, Article 104779. ISSN 1746-8094. https://doi.org/10.1016/j.bspc.2023.104779.

Kannan, S. R., Spratt, A. N., Cohen, A. R., Naqvi, S. H., Chand, H. S., Quinn, T. P., … Singh, K. (2021). Evolutionary analysis of the Delta and Delta Plus variants of the SARS-CoV-2 viruses. *Journal of autoimmunity, 124*, Article 102715.

Katoch, S., Chauhan, S. S., & Kumar, V. (2021). A review on genetic algorithm: Past, present, and future. *Multimedia Tools and Applications, 80*, 8091–8126.

Kopper, P., Wiegrebe, S., Bischl, B., Bender, A., & Rügamer, D. (2022). DeepPAMM: Deep piecewise exponential additive mixed models for complex hazard structures in survival analysis. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining* (pp. 249–261). Cham: Springer.

Kundu, R., Singh, P. K., Mirjalili, S., & Sarkar, R. (2021). COVID-19 detection from lung CT-Scans using a fuzzy integral-based CNN ensemble. *Computers in Biology and Medicine, 138*, Article 104895.

Lao, Z., He, D., Wei, Z., Shang, H., Jin, Z., Miao, J., & Ren, C. (2023). Intelligent fault diagnosis for rail transit switch machine based on adaptive feature selection and improved LightGBM. *Engineering Failure Analysis, 148*, Article 107219.

Lee, C., Yoon, J., & Van Der Schaar, M. (2019). Dynamic-deephit: A deep learning approach for dynamic survival analysis with competing risks based on longitudinal data. *IEEE Transactions on Biomedical Engineering, 67*(1), 122–133.

Meraihi, Y., Gabis, A. B., Mirjalili, S., & Ramdane-Cherif, A. (2021). Grasshopper optimization algorithm: Theory, variants, and applications. *Ieee Access, 9*, 50001–50024.

Parra-Bracamonte, G. M., Lopez-Villalobos, N., & Parra-Bracamonte, F. E. (2020). Clinical characteristics and risk factors for mortality of patients with COVID-19 in a large data set from Mexico. *Annals of epidemiology, 52*, 93–98.

Samanta, B., & Nataraj, C. (2009). Use of particle swarm optimization for machinery fault detection. *Engineering Applications of Artificial Intelligence, 22*(2), 308–316.

Sankareswaran Pandi Senthil, & Krishnan Mahadevan. (2022). Unsupervised End-to-End Brain Tumor Magnetic Resonance Image Registration Using RBCNN: Rigid Transformation, B-Spline Transformation and Convolutional Neural Network. *Current Medical Imaging, 18*(4). https://doi.org/10.2174/1573405617666210806125526

Seidler, M., Forghani, B., Reinhold, C., Pérez-Lara, A., Romero-Sanchez, G., Muthukrishnan, N., … Forghani, R. (2019). Dual-energy CT texture analysis with machine learning for the evaluation and characterization of cervical lymphadenopathy. *Computational and Structural Biotechnology Journal, 17*, 1009–1015.

Senthil Pandi, S., Senthilselvi, A., Gitanjali, J., ArivuSelvan, K., Gopal, Jagadeesh, & Vellingiri, J. (2022a). Rice plant disease classification using dilated convolutional neural network with global average pooling. *Ecological Modelling, 474*, Article 110166. ISSN 0304-3800. https://doi.org/10.1016/j.ecolmodel.2022.110166.

Senthil Pandi, S., Senthilselvi, A., Maragatharajan, M., & Manju, I. (2022b). An optimal self adaptive deep neural network and spine-kernelled chirplet transform for image registration. *Concurrency and Computation: Practice and Experience, 34*(27), Article e7297. https://doi.org/10.1002/cpe.7297

Snider, B., & McBean, E. A. (2020). Improving urban water security through pipe-break prediction models: Machine learning or survival analysis. *Journal of Environmental Engineering, 146*(3), 04019129.

Sun, C. C., Li, S. J., Hu, W., Zhang, J., Zhou, Q., Liu, C., … Li, G. (2019). Comprehensive analysis of the expression and prognosis for E2Fs in human breast cancer. *Molecular Therapy, 27*(6), 1153–1165.

Thorsen-Meyer, H. C., Nielsen, A. B., Nielsen, A. P., Kaas-Hansen, B. S., Toft, P., Schierbeck, J., Strøm, T., Chmura, P. J., Heimann, M., Dybdahl, L. & Spangsege, L. (2020). Dynamic and explainable machine learning prediction of mortality in patients in the intensive care unit: a retrospective study of high-frequency data in electronic patient records. *The Lancet Digital Health*, *2*(4), pp.e179-e191.

Wang, G., Zhou, T., Choi, K. S., & Lu, J. (2020). A deep-ensemble-level-based interpretable Takagi–Sugeno–Kang fuzzy classifier for imbalanced data. *IEEE Transactions on Cybernetics, 52*(5), 3805–3818.

Warrier, H. & Gupta, Y. (2022). Survival Analysis on Structured Data using Deep Reinforcement Learning. *arXiv preprint arXiv:2205.14331*.

Yang, C., Liu, J., Zhou, K., Yuan, X., & Jiang, X. (2023). A meta-path graph-based graph homogenization framework for machine fault diagnosis. *Engineering Applications of Artificial Intelligence, 121*, Article 105960.

Yang, J., Li, Y., Liu, Q., Li, L., Feng, A., Wang, T., … Lyu, J. (2020). Brief introduction of medical database and data mining technology in the big data era. *Journal of Evidence-Based Medicine, 13*(1), 57–69.

Zhang, Y., & Ding, W. (2023). Motor imagery classification via stacking-based Takagi–Sugeno–Kang fuzzy classifier ensemble. *Knowledge-Based Systems*, Article 110292.

Zhao, L., & Feng, D. (2020). Deep neural networks for survival analysis using pseudo values. *IEEE Journal of Biomedical and Health Informatics, 24*(11), 3308–3314.