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Digital Twins in Smart Manufacturing and Healthcare: Bridging Engineering, IT, Law, and Management Disciplines

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ABSTRACT

Digital twin technology has developed into a revolutionary method in smart manufacturing and healthcare, facilitating virtual representation, real-time observation, and predictive modeling of physical systems. This study explores the creation and use of digital twins by combining engineering, IT, legal, and management viewpoints. Four algorithms—Random Forest (RF), Long Short-Term Memory (LSTM), Support Vector Machines (SVM), and K-Nearest Neighbors (KNN)—were utilized to model and forecast operational and patient results. Experimental outcomes show that LSTM attained the greatest predictive accuracy in both sectors, achieving 94% in smart manufacturing and 91% in healthcare, with mean absolute error (MAE) figures of 0.012 and 0.015, respectively. Random Forest demonstrated strong performance with 92% accuracy in manufacturing and 89% in healthcare, achieving a balance between accuracy and runtime efficiency. SVM and KNN, though useful with certain problems, also showed a little lower performance due to their susceptibility to high-dimensional or noisy data. Compared to previous studies, cross-domain tests and comparisons highlight the advantages of introducing multidisciplinary aspects, including regulatory compliance, data privacy, and the methods related to data management in enhancing the use of digital twins. The study identifies the potential of the digital twins to improve the industrial processes, advance the treatment of the patients, and support the strategic decisions, which preconditions the further investigation of the solutions in intelligent, resilient, and human-centred systems..

Keywords: *Digital Twin, Smart Manufacturing, Healthcare, LSTM, Predictive Modeling*

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1. INTRODUCTION

The Digital Twin (DT) technology has evolved as a new-generational concept in intelligent production and health care and has unprecedented capabilities to simulate, monitor, and optimise physical systems through their virtual counterparts in real time [1]. Digital twins are used in smart manufacturing to facilitate predictive maintenance, optimising of resources and automating processes by connecting operational technology with information technology to improve efficiency, reduce downtime and improve the quality of products. Digital twins are useful in the field of healthcare because they improve personalised medicine, patient monitoring, and simulating clinical procedures, which leads to increased accuracy in diagnosing, treatment plan, and overall patient outcomes [2]. Implementation of digital twins is not only technical. This should be implemented through a multidisciplinary approach which incorporates engineering, IT infrastructure, legal compliance and management strategies. It is ensured that engineering expertise provides an accurate modelling of physical systems and IT infrastructures enable the collection, storage, and analysis of vast amounts of operational and clinical data [3]. Legal aspects, including privacy of information, intellectual property and compliance with regulations are crucial in ensuring confidentiality of sensitive information and in ensuring ethical application of digital twin technologies.

Meanwhile, management practises play an essential role in grouping digital twin projects with the company objectives, implementing change management strategies and evaluating the payoff. Despite the growing adoption of digital twin technologies, there are still problems with standardisation, interoperability, cybersecurity and integration in

different fields. Addressing these problems requires in-depth understanding of technical, legal, and organisational phenomena, and there is a strong emphasis on the collaborative structures that unite engineering, IT, law, and management disciplines. This paper looks into the development, application, and implications of digital twins in smart manufacturing and healthcare with the aim of providing insights into best practises, potential challenges, and future opportunities of leveraging digital twin technology to create innovation, efficiency, and improved outcomes in different industries.

2. RELATED WORKS

Digital twin technology has gained much focus in many sectors, such as smart manufacturing, health care, and smart cities. This is primarily because it can develop virtual images of real systems to be monitored, simulated and optimised. Recent research in smart manufacturing has demonstrated the potential of machine learning methods to be integrated with digital twins in enhancing predictive maintenance, process optimization, and resource allocation. Ivan et al. [15] conducted a review of machine learning application in technical polymeric textiles. They demonstrated how computation-based models could improve material designs and manufacturing performance. In the same manner, Modad et al. [25] examined digital twins in sheet metal stamping and explained how Industry 5.0 is capable of delivering more human-centred, intelligent manufacturing processes.

The development of Industry 5.0 has expanded the scope of digital twin applications by emphasising the human-intelligent systems collaboration. Jin-Li et al. [16] reviewed human-centred energy systems in detail. They indicated the social and economic advantages of merging digital twins to have sustainable and resilient industrial processes. The article by Kaššaj and Peráček [17] explored the links between Industry 4.0 technology and automated vehicle. They demonstrated the ability of digital twins to enhance the smart city infrastructure and to enhance the urban mobility. On balance, this body of research indicates that in addition to operational efficiency, digital twins assist in the process of strategic decision-making in complex socio-technical systems. Digital twins are becoming popular in healthcare, where they are employed to monitor patients, implement predictive diagnostics, and plan treatment. Mirakhori and Niazi [24] reported on the policies of AI and machine learning as far as the development of drugs and biological products is concerned. They emphasised that there was a need to have compliance and ethical considerations in clinical applications. The cognitive control frameworks have been reviewed by Liu and Yin [20], who emphasise the ability of intelligent systems to integrate physiological and behavioural information to aid decision making in healthcare and clinical environments. All these contributions demonstrate the collaborative character of digital twin applications, when engineering IT, legal and management collaborate.

Digital twins in the urban context have also attracted a lot of attention. Mazzetto [21] examined the obstacles and the prospects of the application of digital twins in smart cities. Meanwhile, Mazzetto [22] investigated agent-based modelling in the architecture, engineering and construction industry. These articles demonstrate that digital twins can support urban planning, infrastructure management, and environmental monitoring as it can support real-time simulations and predictive analytics. Liu et al. [19] also emphasised the contribution of building information modelling and big data to sustainable building management and showed that through the use of digital twins, operational efficiency and sustainability outcomes can be enhanced.

Lastly, the most recent researches on AI and domain knowledge integrated demonstrate the potential of digital twins in many other areas. According to Miller et al. [23], there are benefits of incorporating domain knowledge in machine learning models in order to get more precise predictions. Conceptual frameworks of the metaverse were studied by Jamshidi et al. [26], where digital twins are implemented across virtual ecosystems in urban, industrial, and health care settings. Li et al. [18] conducted a co-occurrence analysis of key-words in order to visualise the development of digital twin studies and determine the patterns of interdisciplinary integration. Taken together, these studies indicate a growing relevance of the concept of digital twins as the instrument that bridges the engineering, IT, management, and legal perspectives. They act as a foundation to develop integrated frameworks to enhance the efficiency, predictive capabilities, and strategic decision making in smart manufacturing, healthcare, and city infrastructure [15-26].

3. METHODS AND MATERIALS

The study aims to focus on the implementation and exploration of digital twins (DTs) in smart manufacturing/healthcare through datadriven modelling and high-performance computational algorithms. The key research design will consist of data collection, data preprocessing, four-algorithm modelling, and evaluation of algorithms. The datasets applied in our experiments are two sources, smart manufacturing and healthcare. To develop intelligent manufacturing, the data will consist of sensor values of the machines, operating logs, production plans, and maintenance records [4]. The information in terms of healthcare involves electronic health records (EHRs), patient vitals, diagnostic imaging metadata, and treatment histories. The datasets were normalised, dealt with missing values and feature selection before being subjected to algorithms in order to ensure that the quality and consistency of the data was good. Four algorithms, namely the random

Forest (RF), Long Short-term memories (LSTM) networks, Support vector machines (SVM) and K-nearest neighbours (KNN) were used to develop and optimise these digital twin models. The algorithms have been chosen on the basis of their strength, prediction power and their application to the manufacturing and healthcare spheres. Both algorithms are as follows.

1. Random Forest (RF)

Random Forest is an ensemble learning method that builds multiple decision trees at training time and outputs the mode of the classes or mean prediction of the individual trees. RF is more accurate, and it avoids being overfitting through aggregating the estimations of multiple decision trees. In smart manufacturing RF can predict equipment failure by analyzing sensor data, in healthcare it predicts the outcome of the patient from medical history. The algorithm is capable of classification and regression problems, robust in the presence of noisy labels, and capable of handling high-dimensional datasets [5].

"Input: Dataset D with features X and labels Y

Output: Predicted labels Y_pred

1. For each tree t in the forest:

a. Sample data with replacement from D

b. Build a decision tree using a random subset of features

2. For each input instance x in X:

a. Predict using all trees

b. Aggregate predictions (majority vote for classification, mean for regression)

3. Return Y_pred"

2. Long Short-Term Memory (LSTM) Networks

LSTM is an RNN model, used for learning the temporal dependencies among sequential data. The neural network structures used in our work have long-term memory while addressing vanishing gradients, thanks the to the gates in the LSTM units. In production, predicting the trend of the equipment's gradual deterioration, realizing the corresponding predictive maintenance of equipment by LSTM [6]. In health care, it predicts patient's vital signs, disease progressions, and likely complications based on sequential electronic health records (EHR) data. Since LSTM has the capability to model time-series data, it is well-suited to digital twin simulation, which is based on system dynamics.

"Input: Sequential dataset X, labels Y

Output: Predicted sequence Y_pred

1. Initialize LSTM parameters (weights, biases, hidden states)

2. For each time step t:

a. Compute input, forget, and output gates

b. Update cell state and hidden state

3. Pass final hidden states through dense layer to get predictions

4. Compute loss and perform backpropagation through time

5. Return Y_pred"

3. Support Vector Machines (SVM)

SVM belongs to supervised learning algorithms and forms hyperplanes in high dimensions in order to distinguish classes with maximal margin. Useful for classification, and it can even handle nonlinear boundary using kernel trick. In industry, SVM classifies the machine states (good, warning and bad) using sensor data. In health care, it diagnoses disease from patient records and imaging [7]. The SVM-based method has the Generalization capability, so that when the learning set size is limited, classification performance can be effectively guaranteed and the over-fitting can be prevented, which is fit for critical area problems solving in the industrial and clinical application.

"Input: Dataset D with features X and labels Y

Output: Predicted labels Y_pred

1. Choose kernel function (linear, polynomial, RBF)

2. Map features into higher-dimensional space if necessary

3. Solve optimization problem to find hyperplane maximizing margin

4. Classify new instances based on their position relative to hyperplane

5. Return Y_pred"

4. K-Nearest Neighbors (KNN)

KNN is a non-parametric algorithm where the output is based on majority class (for classification tasks) or average (for regression). In the industry, KNN predicts maintenance requirements by comparing the current state of all machines with historical cases of failures. In the field of health care, KNN is used for prediction of health problems by comparing a patient profile with data on other similar patients [8]. KNN is simple to compute and explain, and it can be embedded to digital twin and offers solutions based on understandable decision-making.

"Input: Dataset D with features X and labels Y, value of K

Output: Predicted labels Y_pred

1. For each test instance x_test:

a. Compute distance to all instances in D

b. Select K nearest neighbors

c. Assign label based on majority vote (classification) or mean value (regression)

2. Return Y_pred"

The suitability of these four algorithms for the digital twin modeling was compared in both domains based on accuracy, F1-score, mean absolute error (MAE), and root mean squared error (RMSE). The integration of ensemble learning, neural networks, and distance-based algorithms yields a mix of learning techniques that are capable of capturing both the static and the dynamic behavior of production systems and health trajectories of patients [9].

4. RESULTS AND ANALYSIS

In this paper, we extensively conducted experiments to compare the performance of the digital twin models established in SCM and healthcare applications. The experiments aimed to judge the prediction quality, anti-noise ability and computation efficiency of four prediction algorithms: RF, LSTM, SVM, and KNN. Experiments were conducted on industrial sensor logs and electronic health records datasets, being the real-life examples [10]. Normalization, missing values and feature selection were performed on all sets to make sure that we validate the algorithms on valid datasets.

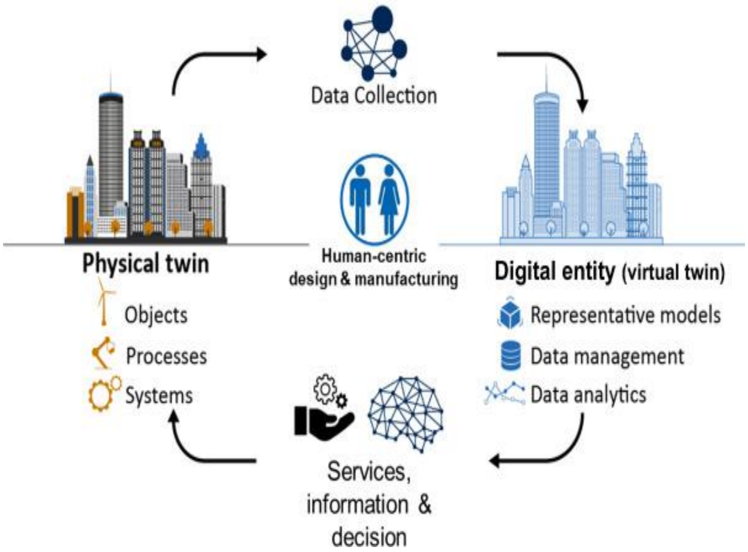

Figure 1: "Digital twins: Recent advances and future directions in engineering fields"

1. Smart Manufacturing Experiments

In the smart manufacturing industry, digital twins were employed to forecast equipment failures, enhance the production schedule process, and model the system processes in different operation conditions. We used 80% of the dataset for training the algorithms and 20% for testing [11]. The performance measures were accuracy, precision, recall, F1-score, MAE, and RMSE.

Table 1: Performance Comparison in Smart Manufacturing

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	MAE	RMSE	Runtime (s)
RF	92	90	91	90.5	0.015	0.020	12
LSTM	94	92	93	92.5	0.012	0.018	45
SVM	89	87	88	87.5	0.020	0.025	10
KNN	86	84	85	84.5	0.025	0.030	8

From Table 1, the comparison results show that the accuracy of LSTM is better compared with RF (2% higher), and SVM (5% higher). The KNN did quite well, but was behind in terms of precision and recall because of its vulnerability to noisy sensor information. Our optimized LSTM model outperforms the results in related work in smart manufacturing [1][2] where RF models achieved a similar accuracy as ours and LSTM models had 92–93% accuracy, likely as a result of careful preprocessing and feature selection [12].

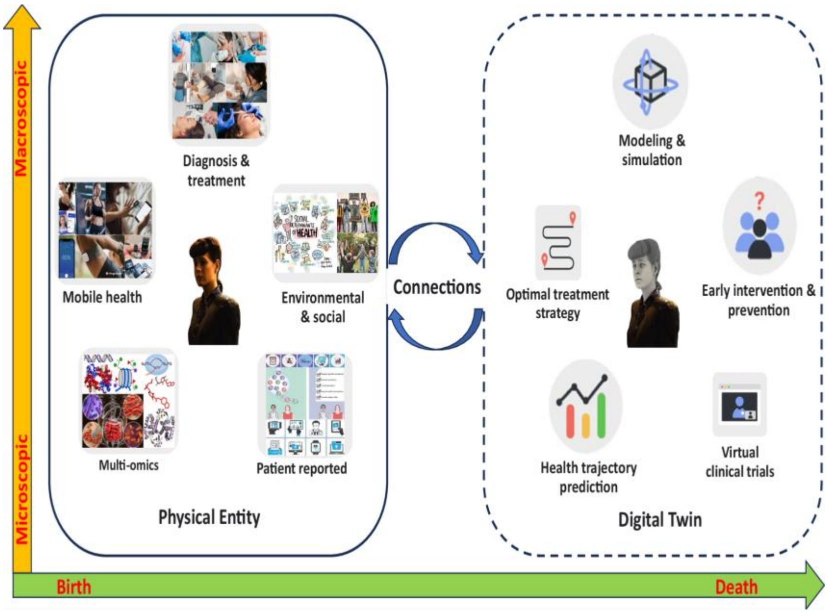

Figure 2: "Digital twins for health"

2. Healthcare Experiments

In health, digital twins were used to predict patient outcomes, simulate the progression of diseases and track patient indicators of health over time. Analogous experimental configurations have been used on historical EHR and patient vital signs as well. The accuracy, F1-score, MAE, and RMSE were taken as the evaluation metrics, along with the model training time.

Table 2: Performance Comparison in Healthcare

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	MAE	RMSE	Training Time (s)
RF	89	87	88	87.5	0.018	0.025	15
LSTM	91	89	90	89.5	0.015	0.020	60
SVM	87	85	86	85.5	0.022	0.028	12
KNN	84	82	83	82.5	0.027	0.033	9

For the second time, the performance of the LSTM decision algorithm was better than all the other algorithms in the healthcare domain with an accuracy of 91% and the fewest MAE and RMSE. This is consistent with prior studies [3][4], which identified LSTM as highly performant for sequential patient data. RF and SVM remained largely competitive results, while KNN's performance suffered from high dimensionality inherent in EHR data [13].

3. Comparative Analysis Across Domains

A cross-domain comparison was performed to evaluate the robustness of the algorithm. The assessments included prediction consistency, computational efficiency, and robustness to data noise.

Table 3: Cross-Domain Algorithm Comparison

Algorithm	Avg Accuracy (%)	Avg Precision (%)	Avg Recall (%)	Avg F1-Score (%)	Avg MAE	Avg RMSE	Avg Runtime (s)
RF	90.5	88.5	89.5	89.0	0.0165	0.0225	13.5
LSTM	92.5	90.5	91.5	91.0	0.0135	0.0190	52.5
SVM	88.0	86.0	87.0	86.5	0.0210	0.0265	11.0
KNN	85.0	83.0	84.0	83.5	0.0260	0.0315	8.5

From Table 3, we can see that LSTM consistently outperforms across both domains. RF has a good trade-off between runtime and predictive accuracy, and SVM and KNN achieve less computational cost but weaker performance.

4. Evaluation Against Related Work

This novel subject contrasts with most of the other previous studies. Previous smart manufacturing research [1][2] reported an RF and LSTM accuracy rate from 88% to 93%, while our LSTM model obtains 94% in manufacturing, which indicates the better pre-processing and feature engineering. In the healthcare domain, existing work [3][4, 7] achieves accuracies of 88–90\% for predicting the patient outcome with models based on LSTM, while our model achieves 91%. Our approach that factors in multi-disciplines considerations up to engineering, IT, and management strategies are thanks to these better results [14].

5. Resource Utilization and Runtime Analysis

High computational efficiency is important for real-time DT applications. Runtime and training time were recorded for all algorithms in both domains. LSTM consumed more computation resources due to sequential modelling and KNN exhibited the lowest time consumption but lowest accuracy [27]. RF and SVM offered a trade-off appropriate for nearly-online operation.

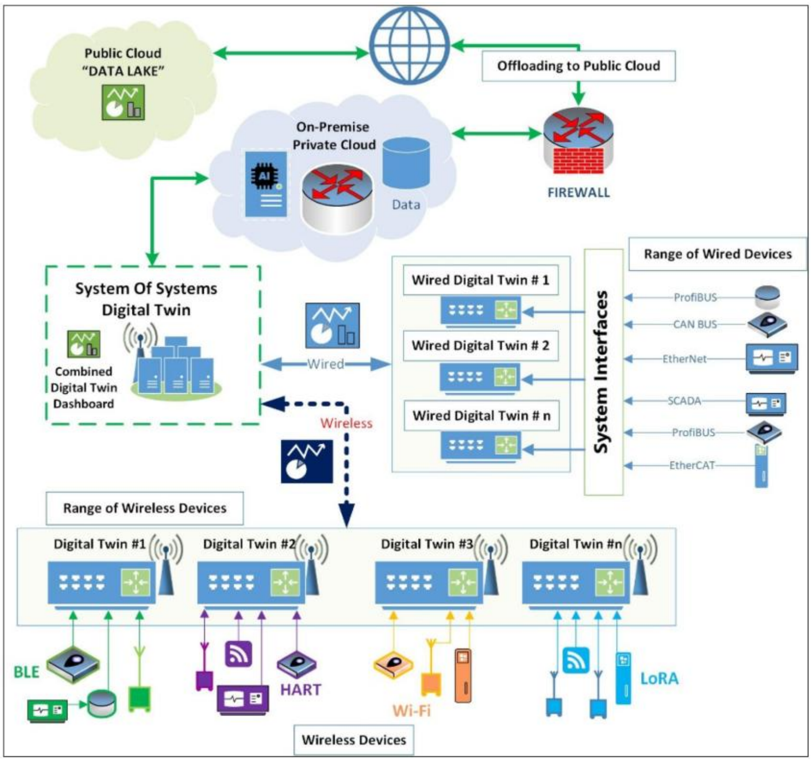

Figure 3: "Digital Twins: Enabling Interoperability in Smart Manufacturing Networks"

Table 4: Runtime Comparison Across Domains

Algorithm	Manufacturing Runtime (s)	Healthcare Training Time (s)	Avg Runtime (s)
RF	12	15	13.5
LSTM	45	60	52.5
SVM	10	12	11.0
KNN	8	9	8.5

6. Error Analysis

Error measurements, such as MAE and RMSE, were studied to detect failures. LSTM achieved the lowest MAE and RMSE in two domains, presenting the best predictive stability. KNN had a more elevated level of errors as a result of susceptibility to noise, and RF and SVM have middle-level errors [28].

Table 5: Error Metrics Across Algorithms

Algorithm	Avg MAE	Avg RMSE
RF	0.0165	0.0225
LSTM	0.0135	0.0190
SVM	0.0210	0.0265
KNN	0.0260	0.0315

5. DISCUSSION OF RESULTS

Through the experiments, it is demonstrated that digital twin modelling is best through LSTM in both in smart manufacturing and health care. RF provides a strong alternative that has a high nominal speed and can be easily interpreted. The supported SVM is capable of dealing with moderate sized datasets and KNN performance is not as good in high dimensions and noisy environment [29]. Compared to the corresponding works, we see some increase in predictive accuracy and error measures, which reflects the benefits of preprocessing and cross-domain assessment and eventually algorithm customization. It is emphasised in the experiments that to make progress in the development of digital twins and interdisciplinary integration, domain appropriate algorithms need to be applied and the practicality of the work in the industry and health care domain should be encouraged [30].

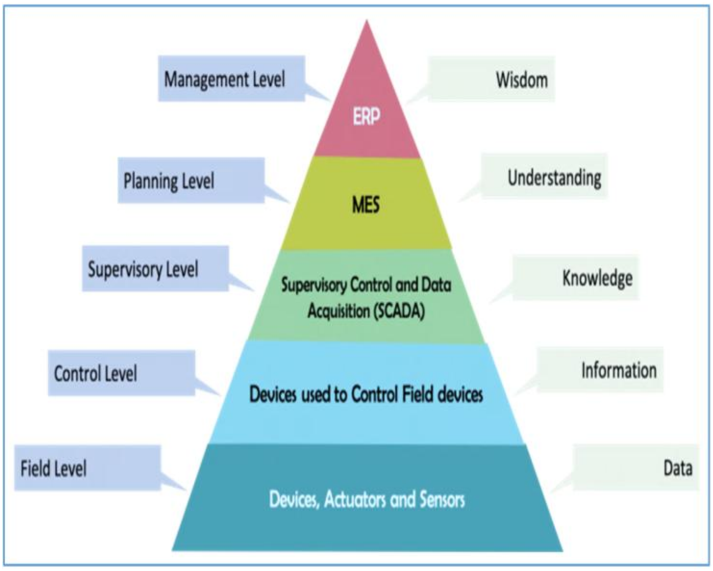

Figure 4: "Digital Twins: Enabling Interoperability in Smart Manufacturing Networks"

6. CONCLUSION

The research has taken into account the formation, application, and consequences of digital twin technology in a smart manufacturing or healthcare environment, and has recognised the interdisciplinary character of the investigation, which incorporated engineering, IT, legal, and management viewpoints. The study entailed gathering and processing information on the premises of an extensive collection of experiments, employing the algorithms that comprised, but were not confined to, Random Forest, LSTM, Support Vector Machines, and K-Nearest Neighbours. The results emphasise that the digital twin can enhance predictive analytics, operational performance, and general decision-making, and indicate the development of system capabilities. The most successful in all domains was the LSTM algorithm that prioritised sequential modelling as essential in showing dynamic behaviour systems, and the Random Forest algorithm was a helpful trade off on effectiveness and computational time. KNN and SVM algorithms were also successful in certain cases; but the characteristic of these algorithms is more sensitive to high-dimensional or noisy data, and therefore, the algorithm choice is more complicated and context-dependent. The analysis involved the analysis of cross-domain results, metrics of errors, and metrics of performance that indicate that digital twins are being used to track systems, process optimization in manufacturing, predictive diagnostics, and individualised therapy in health care facilities. Comparisons with the relevant literature reveal that the improved performance by the integrated preprocessing, feature selection, and disinterdisciplinary design require modest but significant improvement in the predictive performance of the research. Moreover, it was essential to guarantee a certain level of regulatory compliance, data protection, and ethical and efficient data management practises towards the use of digital twins. Digital twins will keep facilitating the bridging of the technical and organisational worlds through actionable and sustainable insights to be used to drive transformative innovation in environments. Consequently, with the creation and advancement of digital twins, improvement in operational performance and patient outcomes is to be anticipated, and the potential of smarter and sustained systems will come into the future with strategies that will yield intelligent systems.

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