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Empowering Cyber-Physical Systems through AI-driven Fusion for Enhanced Health Assessment

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ABSTRACT

Cyber-physical systems (CPS) for improved health assessment currently face multiple challenges with managing and treating health issues, and there is an uncontrollable amount of risk, as well as the requirement for effective artificial intelligence (AI) algorithms that can manage complex and dynamic health data. In this paper, we provide Hybrid Support Vector Machines fine-tuned Spatial Transformer Networks (HSVM+FSTN) for the prediction of enhanced health assessment. 299 cardiac failure patients were gathered in the Kaggle source, and the data was pre-processed using Z-score normalization. Linear discriminant analysis was employed for feature extraction. Classification was provided for both the machine learning (ML) and deep learning (DL) techniques. The performance analysis was carried out on the Python platform. The proposed HSVM+FSTN performance was more significant when compared to existing techniques in terms of sensitivity (95.4%), accuracy (97.2%), specificity (94.4%), and precision (96.7%).

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1. INTRODUCTION

The integration of physical processes and computing methods leads to cyber-physical systems (CPS) that are interconnected systems with instantaneous monitoring and control capabilities [1]. Ambient sensors and wearable technology have been utilized more and more in healthcare applications. Protocols for routing can be selected based on the layout of each application, which is different [2]. Healthcare 5.0 has been significantly impacted by the Internet of Things (IoT). IoT-enabled health devices are frequently employed by healthcare facilities to share patient information online [3]. A multitude of interrelated industrial ecosystems can benefit from the integration of information technology and operation technology systems into CPSs. It presents potential vectors, such as Man-in-the-Middle (MITM), that present issues [4]. Hospitals can immediately move outpatients into less congested treatment facilities with the application of health prognostic systems. It increases the number of patients receiving health care in hospitals. A fitness prediction system explains the frequent issue of sudden fluctuations in hospital patient patterns [5]. The objective of the study is to provide enhanced health assessment by employing the HSVM+FSTN technique and the CPS in healthcare as an effective method.

2. RELATED WORKS

The study provided an approach to create images with generative adversarial networks (GANs)[6] that cannot result in checkerboard defects. Research findings demonstrate the suggested method's effectiveness, and it is combined with different GANs to create images. To enhance IoT network security, an innovative kernel homomorphism two-fish encryption technique was combined with an exponential Boolean spider monkey algorithm [7]. Employing the suggested technique was effective in protecting health records. For transferring security in health descriptions, [8] a novel "simplified swarm-optimized Bayesian normalized neural networks (SSO-BNNN)" was developed. Based on experimental data, the model sent the recommended results with the maximum specificity, accuracy, and sensitivity. To present IoT-CPS [9] research that can be used to identify patient ailments using AI. The research observations show that the suggested AI-based IoT-CPS technique more effectively detects patient illnesses and crashes in the elderly compared with existing algorithms. To establish the framework of concepts for automation usage that provides both technical and human levels of support to increase resilience with AI. The outcome delivered an innovative, hierarchical and developed conceptual structure that is capable of assessing the evolution of AI-driven decision-making in CPS [10]. Utilizing supervised machine learning and "Cryptographic Parameter Encryption and Decryption (CPBE&D)" techniques [11], they provided an efficient hybrid validation, secure information, and protection framework that makes certain the identification of reliable IoMT-based CPS during protected transmission of information over the wireless communication channel. Significant security characteristics in terms of economic validation have been demonstrated by the CPBE and D and supervised machine learning (SML) identification techniques during the examination of the simulation results. The backpropagation neural network (BPNN) [12] was used by the environmental information computation module to identify patterns and categorize data.

The research on the implementation of AI and CPS can provide an intellectual basis and useful sources of information for the growth of the smart construction field. To examine the risks and possibilities that AI and CPS could represent for modern economies and civilizations [13]. The connected possibilities for unmanned aerial vehicles (UAV) primarily involve creative applications in inaccessible fields, presenting significant risks to human life and health. To develop an efficient CPS, [14] conducted an extensive evaluation of wireless sensing and "structural health monitoring (SHM)" technologies. SHM, based on "wireless sensor networks (WSNs)", has the ability to reduce the requirements for infrastructure construction and operation in the public and private sectors. Given the simple implementation and significant savings in costs, WSN networks potentially led participants in solving several SHM issues. The research [15]examined the issue of CPS dependability by modelling the CPS-IoT monitoring process using mathematical epidemiology. It suggested an innovative reconfiguration protocol that applied node migration between clusters and network separation through clustering to recover the security of CPS-IoT subsystems. These findings were obtained from the experimental outcomes of the suggested interference-aware clustering protocols with node migration.

3. MATERIALS AND METHODS

In this portion, data collection and pre-processing were explained. The classification provides innovative hybrid support vector machines with fine-tuned spatial transformer networks (HSVM+FSTN). Figure 1 depicts the methodology flow.

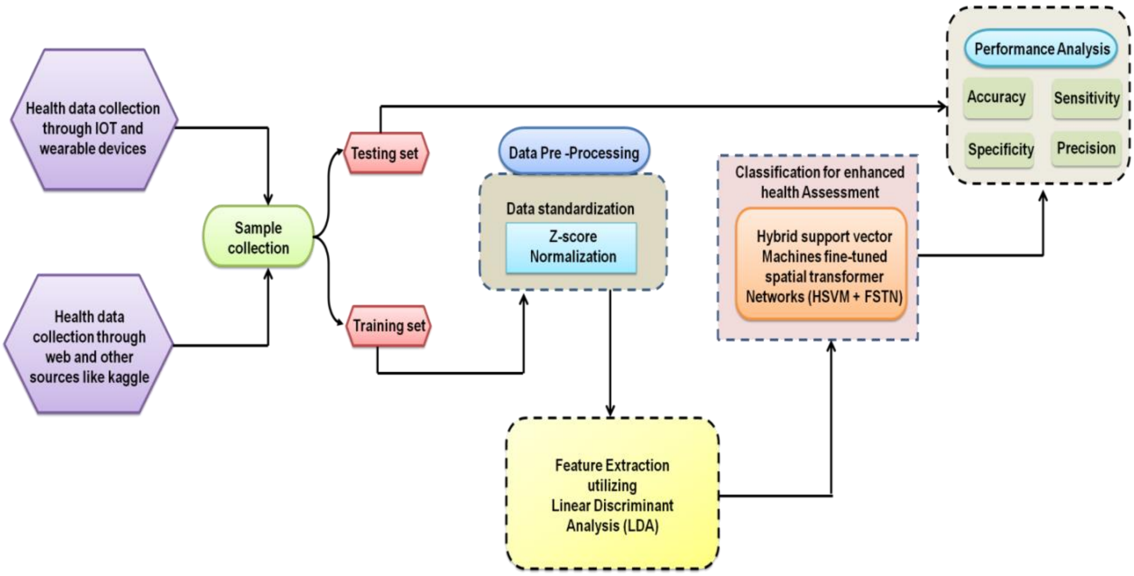

Figure 1. Flow of Proposed Methodology

3.1. Sample Collection

The Kaggle dataset was used in our technique [16]. The dataset has 299 rows and 12 columns. The features and the desired variable are shown within the columns. The following are the feature variables: sex, smoking, high blood pressure, platelets, anaemia, the CPK, diabetes, fraction of ejection, serum creatinine, and salt levels. There are 299 cardiac failure patients in the dataset. For instance, we employed ML and DL methods to identify cases of cardiovascular disease.

3.2. Data Pre-processing using Z-score normalization

The heterogeneous data from various sensor sources needs to be processed to reduce anomalies and inconsistencies as before the HSVM+FSTN models are trained. The Z-Score normalization technique, frequently referred to as standardization, reconstructs a dataset, ensuring that its average is 0 and its Standard Deviation (SD) is 1. Similarity between several variables or factors is frequently employed in ML and statistics. The Z-Score normalization equation for dataset data point a is as follows (depicted in Equation 1).

$$Z = \frac{a-\mu}{\sigma} \tag{1}$$

The initial part of the data is represented by a, μ denoted the mean or average of the dataset. Z Indicates the constant value, and the standard deviation is indicated by σ.

3.3. Feature Extraction Utilizing Linear Discriminant Analysis (LDA)

Linear discriminant analysis (LDA) is an efficient method for managing variations in class frequencies efficiently. Using the findings of randomized testing, the effectiveness has been evaluated. It provides the greatest connection for each batch of data by reducing the ratio of within-class variance to between-class variation. Constructing an LDA approach was determined by the need to offer a classification that is more precise in comparison to Principal Components Analysis (PCA). Initial data sets can be moved to a different location using PCA without affecting the size, position, or shape and improved class separability and the establishment of a decision-making gap between existing classes.

Utilizing the LDA technique to address two-class issues provides estimation vectors in the space of features that maximize the dispersed matrix throughout categories and reduce the scatter matrix within classes.

$$z = x_1 v_{i_1} + x_2 v_{i_2} + x_3 v_{j_3} + \cdots . x_o v_{j_o} \tag{2}$$

$$a^t = [\{a_1, a_2, \ldots., a_o\}] \tag{3}$$

The vector of coefficients that has to be identified and

$$v_j = \left[v_{j_1}, v_{j_2}, \ldots., v_{j_o}\right] \tag{4}$$

$$v_j = \left[v_{i_1}, v_{i_2}, \ldots., v_{i_o}\right] \tag{5}$$

The normality and collinearity assumptions need to be maintained to estimate the dataset's mean and variance.

3.4. Classification for Enhanced Health Assessment by Employing Hybrid Support Vector Machines Fine-tuned Spatial Transformer Networks (HSVM+FSTN)

We combine two techniques, ML and DL techniques, such as Hybrid support vector machine (HSVM) and Spatial Transformer Networks (STN), for the performance to enhance health by empowering the CPS through AI. The combined techniques form Hybrid Support Vector Machines fine-tuned Spatial Transformer Networks (HSVM+FSTN), and this technique is more effective in performing the function.

3.4.1. Hybrid Support Vector Machines (HSVM)

The Hybrid support vector machine (HSVM) for the unbalanced binary categorization issue is based on the hyper-plane, also referred to as the decision function. As declared as,

$$w(b) = v^C b + q = 0 \tag{6}$$

Utilizing a hybrid vector $v \epsilon L^N$ and bias$q \epsilon L$. The HSVM with the largest margin hyper-plane is represented by the constrained issue as follows:

$$\underset{v, q, \beta_-, \beta_+}{min} \frac{1}{2}\|v\|^2 + y_- \beta_- + y_+ \beta_+ s.t.B_- v + y_- q \leq y_- - \beta_- B_+ v + y_+ q \leq u_+ - \beta_+ \beta_- \geq 0 \tag{7}$$

The regularization term $\frac{1}{2}\|v\|^2$ represents the maximum margins of two parallel hyperplanes. The penalty parameters for managing the weights among components of the positive and negative categories are y_+ and y_-. The positive and negative categories' slack variables are $\beta-$ and $\beta+$. The vectors utilized for the negative categories and the positive ones appear as $y_-$and y_+as well as the training matrices of the negative categories and the positive category are indicated by B_- and B_+.

3.4.2. Spatial Transformer Networks (STN)

An input image or map of features from the convolution network is sent into an STN network. The input becomes exposed to an affine modification and bilinear interpolation to obtain the STN's output. The affine transformation permits the input to be rotated, distorted, and enlarged. The localization network e_{loc} is utilized to predict the transformation's parameters:

$$e_{loc}(J) = X_0 = \begin{bmatrix} \theta_1 & \theta_2 & \theta_3 \\ \theta_4 & \theta_5 & \theta_6 \end{bmatrix} \tag{8}$$

Where matrix H sets the affine transformation, and J is the SPN's input with shape $[H \times W \times C]$ (height, width, channels). Applying the affine transformation to a mesh grid $H \in O^{g \times z}$:

$$H = \{(b_1, a_1), (b_1, a_2), \dots., (b_2, a_1), (b_2, a_2), \dots, (b_z, a_{g-1}), (b_g, a_z)\} \tag{9}$$

z and g do not always have to match H and W. The grid has established that the points between $(b_1, a_1) = (-1, -1)$ and $(b_g, a_z) = (+1, +1)$ are evenly distributed. After implementing the affine modification on H, the image T is created, indicating that to select points in J and transfer them back to H:

$$T_{ji} = X_0 \begin{bmatrix} b_j \\ a_i \\ 1 \end{bmatrix} \tag{10}$$

Where one has been assigned to each point, bilinear interpolation is employed to interpolate each point in S since the mapped points in T do not precisely match one pixel in J. The bilinear interpolation's sub-gradients are specified, and the variables are in e_{loc} by using conventional backpropagation with the transformation.

Reducing the Sample Size: Modifying g and z can modify the backpropagation of sampled points. The data sent to the STN can be down-sampled when g and z are smaller than H and W. $d$is greater than 1, the input gets down-sampled. It indicates the downsample with D. The quantity of points sampled from J is:

$$m_{points} = \left(\frac{H}{D}\right) \cdot \left(\frac{W}{D}\right) = \frac{H \cdot W}{D^2} \tag{11}$$

The sampled points for 2D images decrease quadratically with D.

4. PERFORMANCE ANALYSIS

On an Intel i7 CPU running Windows 7 and equipped with 16 GB of RAM, experiments are executed. Python representations are the source of applications. Several experiments have been performed in this portion to determine the effectiveness of the proposed model. Table 1 describes all of the evaluation parameters that have been utilized in the examination. Comparison with existing techniques [17], including the fuzzy k-nearest neighbour method (F-KNN), modified k-nearest neighbour (MKNN), k-nearest neighbour (KNN), and decision tree (DT) was performed for precision, specificity, accuracy, and sensitivity. The results were presented and discussed. Table 2 depicts the outcomes of existing and proposed methods.

Accuracy is the ratio of true predicted instances to all occurrences. It is a significant performance metric for utilizing imbalanced datasets as it shows occurrences when false positive (FP) and false negative (FN) values are equivalent. Figure 2 shows a comparison of the accuracy of the proposed and existing methods. HSVM+FSTN show the accuracy (97.2%), whereas F-KNN (85.7%), M-KNN (83.9%), DT (75.3%) and K-NN (77.7%) of accuracy. In comparison with existing techniques, the HSVM+FSTN method greatly improved.

Table 1. Evaluation Parameters

Parameters	Equations
Precision	$Precision = \frac{TP}{FP + TP}$
Sensitivity	$Sensitivity = \frac{TP}{TP + FN}$
Accuracy	$Accuracy = \frac{TP + FN}{TP + FP + FN + TN}$
Specificity	$Specificity = \frac{TN}{TN + FP}$

Table 2. Comparison outcomes of proposed and existing methods

Methods	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
F-KNN	85.7	83.93	85.5	84.8
M-KNN	83.9	78.9	81.9	80.7
K-NN	77.7	69.5	75.4	74.21
DT	75.3	75.5	75.6	75.7
HSVM+FSTN [Proposed]	97.2	96.7	95.4	94.4

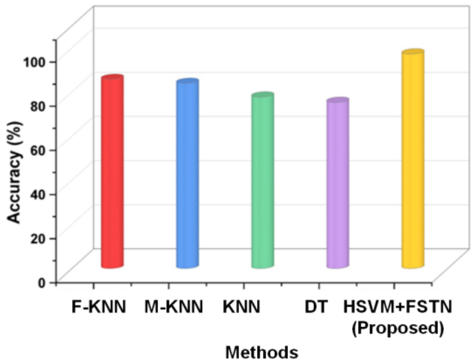

Figure 2. Comparison outcomes of accuracy

Precision is measured as the proportion of correctly anticipated positive predictions to all positive forecasts. Precision is included in predicting the percentage of identified issues. Figure 3 compares the preciseness of the proposed technique with the conventional techniques. HSVM+FSTN shows precision (96.7%), whereas F-KNN (83.93%), M-KNN (78.9%), K-NN (69.5%), and DT provide 75.5% of precision. When compared with the existing techniques, the HSVM+FSTN approach significantly enhanced the field of empowering cyber-physical systems for the enhancement of health.

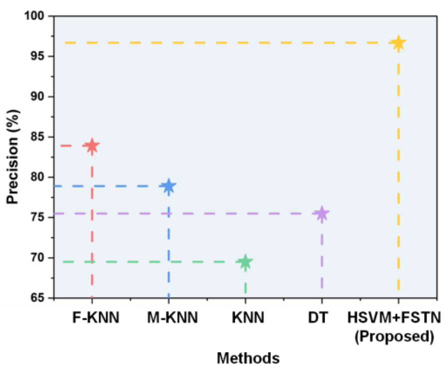

Figure 3. Comparison outcomes of precision

Sensitivity is a data that can be differentiated from various datasets by computing the ratio of real positive to all real instance that are positive. In Figure 4, the sensitivity values are displayed. The sensitivity of the HSVM+FSTN approach is 95.4% when compared to our proposed approach and F-KNN (85.5%), M-KNN (81.9%), DT (75.6%) and KNN (75.4%). The proposed approach enhances health assessment by empowering cyber-physical systems.

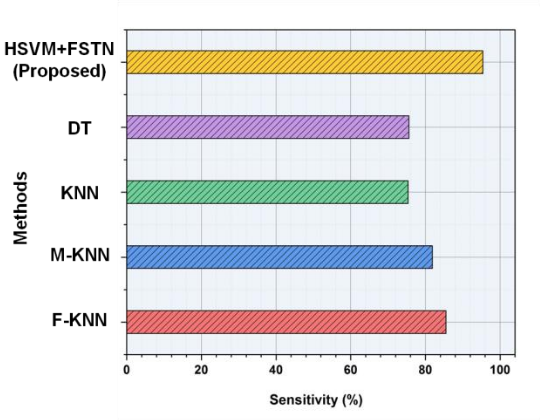

Figure 4. Comparison outcomes of sensitivity

Specificity quantifies a model's capacity to precisely identify each significant negative circumstance identified in a dataset. Figure 5 emphasizes the importance of both specificity values. The specificity of the proposed HSVM+FSTN approach increased by 94.4% when compared to existing methods like F-KNN (84.8%), DT (75.7%), M-KNN (80.7%), and KNN (74.21%). The proposed technique enhances health in cyber-physical systems by comparing HSVM+FSTN with conventional methods.

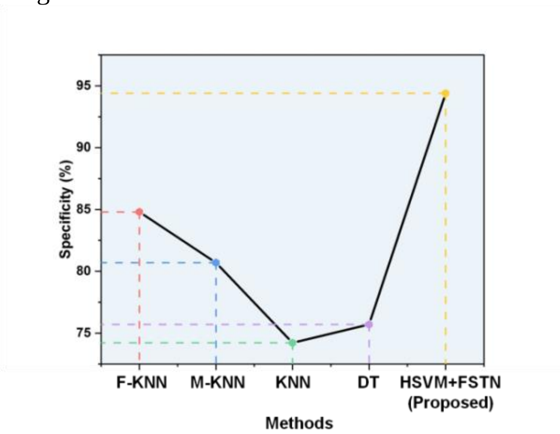

Figure 5. Comparison outcomes of specificity

5. CONCLUSION

This paper provided a novel, highly effective CPS through AI-driven fusion for an enhanced health assessment system with the combination of ML and deep learning DL techniques of HSVM+FSTN network models.299 individuals with cardiac disease are included in the Kaggle dataset that was utilized for the research. Z-score normalization was employed as a pre-processing step to standardize the data, and then the median filter was applied to reduce noise. The classification process employs CPS to perform a function implementation for health improvement by combining the ML and DL methods. Then, we compared the proposed HSVM+FSTN method with various existing methods to demonstrate its effectiveness. The efficiency of HSVM+FSTN in the comparison outcomes is as follows: precision (96.7%), specificity (94.4%), accuracy (97.2%), and sensitivity (95.4%). To accurately determine the latest phase of equipment degeneration, predictive maintenance CPS systems can make use of data collection and calculations. In further research, incorporating AI-driven fusion to CPS enables improved health assessments for more accurate diagnosis and preventative treatment.

DATA AVAILABILITY STATEMENT

The original data presented in the study are openly available in Kaggle at https://www.kaggle.com/code/habibmrad1983/heart-failure-prediction-habib-mrad

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest in this work.

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Adnène Arbi is a distinguished academic affiliated with the University of Carthage in Tunisia, where he has contributed significantly to the fields of mathematics and engineering. His tenure at the university spans over a decade, during which he has held various positions, including roles at the Ecole Polytechnique de Tunisie and the Ecole Nationale des Sciences et Technologies Avancées de Borj Cédria. His research interests primarily focus on neural networks, dynamical systems, and mathematical modelling, with a particular emphasis on the stability and controllability of complex systems. Arbi's recent publications reflect his commitment to advancing knowledge in applied mathematics. Notable works include investigations into Morlet wavelet neural networks and the dynamics of delayed cellular neural networks, showcasing his expertise in both theoretical and practical aspects of mathematical sciences. His research has been published in reputable journals, contributing to the understanding of nonlinear systems and their applications in various domains, including the modelling of COVID-19 dynamics. In addition to his academic pursuits, Arbi has collaborated with several prestigious institutions worldwide, including the

University of the Witwatersrand and Imperial College London, enhancing his research impact and fostering international academic partnerships. His work continues to inspire students and researchers alike, solidifying his reputation as a leading figure in the mathematical community. He can be contacted at email: adnen.arbi@gmail.com.

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