International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Pragmatic Review of Learning Models Used for Unsupervised Analysis of Existing Cyber Physical Deployments from an Empirical Perspective

Varsha Haridas Sadrani [1]*, G. V. V. Jagannadha Rao [2]

Submitted: 20/12/2023 **Revised**: 31/01/2024 **Accepted**: 10/02/2024

Abstract: Cyber-physical deployments include game engines, multimedia systems, internet of Things (IoT) systems, etc. Each of these models has certain inputs, several processing layers, and certain outputs. Monitoring & control of such deployments can be automated via their unsupervised analysis, which requires deep learning & pattern analysis methods. A wide variety of such models are proposed by researchers and system designers, but each of them has its own nuances, advantages, limitations, & future research scopes. Moreover, these models have different performance characteristics, that vary in terms of analysis accuracy, precision, recall, fMeasure, delay of analysis, response time, computational complexity, etc. Thus, while deploying such learning models, researchers & system designers are required to perform manual analysis, validation, and testing for automation & control. Due to this cumbersome process, the cost & time to market for these unsupervised control models is very high, which limits their scalability, and deployment capabilities. To overcome this issue, a detailed characteristic discussion of these models is done in this text. Based on this discussion, researchers will be able to identify existing unsupervised & semi-supervised learning models, which closely match their deployments. These models are further analyzed in terms of their performance metrics, that includes, accuracy of analysis, response time needed for control, delay needed for analysis, precision of analysis, computational complexity, and cost of deployment. Using these metrics, researchers can evaluate best performing models for their deployments, which will assist them in reducing cost, and time needed for automating their cyber physical systems. This text also discusses certain future prospects that can be explored by researchers in order to further enhance quality of their deployments.

Keywords: *Neural, Network, Cyber, Physical, Unsupervised, Scalability, Empirical, Complexity, Automation, Control*

1. Introduction

Design of automation controllers for cyber physical systems is a multidomain task, which involves design of methods for input pattern analysis, response analysis, control signal analysis, etc. A typical automation controller [1] for such systems can be observed in figure 1, wherein different inputs are controlled via an input analysis engine, which assists in analysis of different input signals. Signals are generated based on this analysis, and are given to the plant model, which uses design requirements & automatic control engine design tools in order to produce a control design for the model. This design is used to develop a control model, that is capable of automatically controlling the entire plant (or control system) deployment.

1 Research Scholar, Department of Mathematics, Kalinga University, Raipur rain4meonly@gmail.com
2 Department of Mathematics, Kalinga University, Raipur
gvvjagan1@gmail.com

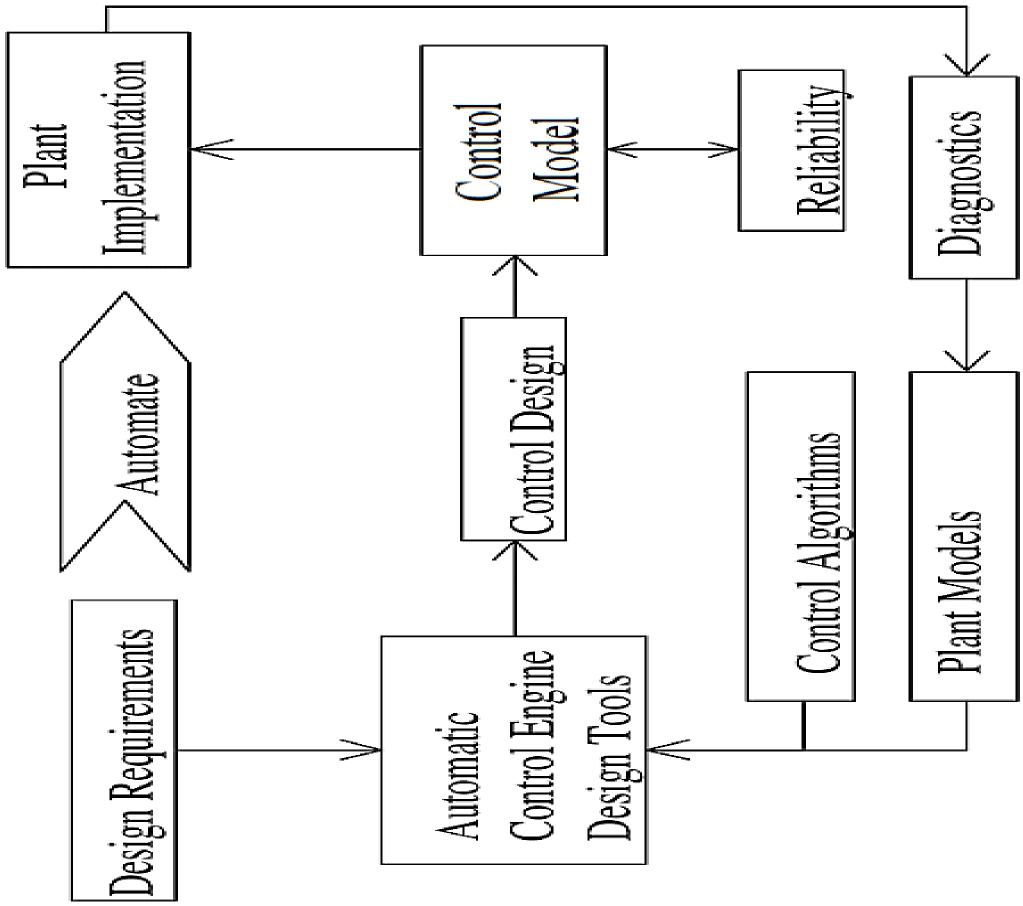

Fig 1. Design of a typical model for automation of control systems

In some models, feedback is also taken from the cyber physical system, which assists in estimating its performance variation due to the deployed control system for different input combinations. Based on this feedback, the model is tuned, and continuous performance enhancement is achieved, which assists in improving underlying model performance under different input & output conditions. Similar models [2, 3, 4], along with their nuances, advantages, limitations, and future research scopes are discussed in the next section of this text. Based on this discussion, readers will be able to identify close similarities with their own deployment models, which will assist them in short listing models that suit their interface requirements. After this discussion, section 3 further analyzes these models in terms of statistical performance metrics that include, accuracy of analysis, response time needed for control, delay needed for analysis, precision of analysis, computational complexity, and cost of deployment under different scenarios. Upon referring to this performance evaluation, researchers will be able to select the best performing model for their deployment, and use it for high-efficiency automation purposes. Finally, this text concludes with some interesting observations about the reviewed models, and recommends methods to further improve their performance.

2. Pragmatic review of unsupervised learning models

Researchers have proposed a wide variety of unsupervised learning methods, which can be used for solving multidomain tasks including classification, clustering, prediction, etc. Each of these models have their own characteristics, and are deployed for context-specific applications. For instance, work in [1] proposes use of Incremental & Unsupervised Domain-Adversarial Neural Networks (IUDANN), which are highly flexible and can be used for prediction of output combinations via pattern analysis of different input types. The model uses a combination of feature extraction layer with label classifier to obtain classification outputs. These outputs are further tuned via use of domain classifiers which assists in estimation of error functions. IUDANN Models use gradient reversal layer (GRL) to tune their internal training constants to reduce these error functions. Working of this model is depicted in figure 2, wherein inputs, their intermediate processing layers, and output classes are visualized, and can be applied to multiple scenarios.

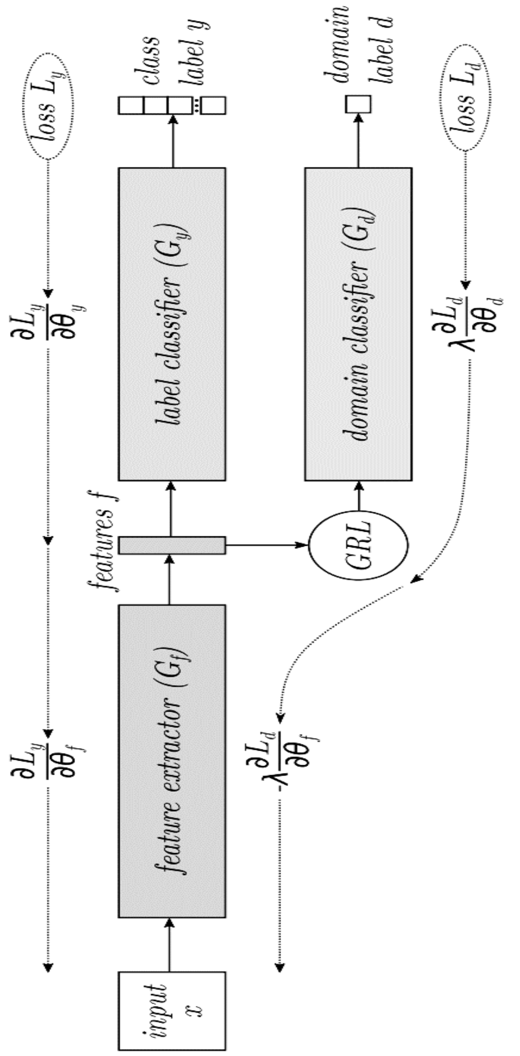

Fig 2. Design of IUDANN for continuous performance optimizations [1]

This model is applied for Optical Character Recognition (OCR), Number Plate Recognition, and other applications that involve 2D input datasets. But it can be extended for other applications via internal parameter tuning and cross validations. The model showcases an accuracy of 96.95% for multiple applications, which is higher than Convolutional Neural Network (CNN) (57.53%), DANN (68.23%), improved CNN (iCNN) (72.62%), and iDANN (85.91%), thus recommending use of IUDANN for large-scale deployments. But efficiency of this model is limited when applied to 1D or 3D datasets, which makes it useful for image processing applications. To overcome this limitation, work in [2] proposes use of two-stage unsupervised multiple kernel extreme learning machine (TUMK-ELM) which assists in data extraction from multiple sources to perform closed-loop learning under heterogeneous datasets. To perform this task, multiple types of kernels are deployed, such that each kernel is capable of solving single task with high efficiency, which improves overall performance via k Space data construction, and kernel combination coefficients (kCCs). These values are processed via use of an ELM based engine as depicted in figure 3, which assists in continuous tuning of kCCs via an incremental learning process.

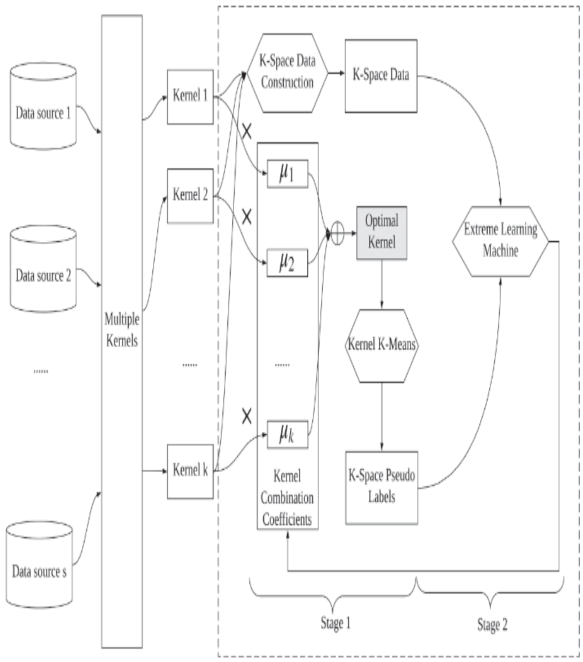

Fig 3. Design of TUMK-ELM for heterogeneous data processing [2]

Due to continuous learning, the proposed model is capable showcases an accuracy of 93.5%, which is higher than Robust Multiple Kernel K Means (RMKKM) (85.5%), and Linear MKKM (LMKKM) (86.4%) models, which makes the underlying model useful for large-scale deployments. But the model requires implementation of multiple kernel types, which increases its computational complexity. To reduce this complexity, work in [3] proposes use of Unsupervised Cross View Metric Learning (UCVML), which can be used for 2D & 3D datasets. The model uses shared mapping for exploration of shared features via estimation of Nonparametric Maximum Mean Discrepancy (NMMD) metrics, that is used for domain adaptation & transfer learning operations. The model showcases an accuracy of 96.2% on different datasets, which is higher than Cros

View Quadratic Discriminant Analysis (XQDA) (75.4%), Cross View Discriminant Component Analysis (CVDCA) (83.5%), and Clustering-based Asymmetric Metric Learning (CAMEL) (85.5%) under different datasets. This model requires larger training data, thus is only applicable for big data applications, thus it needs to integrate data augmentation to improve its scalability performance. Augmentation models are capable of deployment for small scale to large scale applications, which increases their deployment capabilities. Such models are discussed in [4], wherein researchers have proposed use of Artificial Neural Network (ANN), Hierarchical Cluttering, Bayesian Clustering, Partitional Clustering, Mixture Distribution, Blind Signal Separation, Hidden Markov Model (HMM), Probabilistic Graph Models (PGMs), Generative Topographic Model (GTM), Nonlinear Clustering with Multidimensional Data (NCDM), Auto Encoders (AE), Self-Organizing Kohonen Maps (SOKM) and Stochastic Neighbour Estimation (SNE). These models are applied to network applications, but can be extended for other classification & post-processing tasks. It was observed that ANN achieved an accuracy of 83.5%, HMM showcased an accuracy of 79.8%, PGMs had an accuracy of 75.4%, NCDM achieved an accuracy of 64.5%, SOKM showcased an accuracy of 85.5%, while SNE had an accuracy of 74.9% on different datasets. These models must be validated on multiple datasets, and their performance can be improved via application of sparse coding & other deep learning techniques. Such a technique is discussed in [5], which proposes use of Unsupervised Transfer Learning using Multiple Scaled Convolutional Sparse Coding (UTL MSCSC) for medical applications. The model uses different filter sets to extract features, which assist in continuously improving its training & validation performance. Flow of the model is depicted in figure 4, wherein Colour Decomposition (CoD), Multiple Scale Convolution, Absolute Value Rectification at element level (Abs), Local contrast normalization (LCN) and Max Pooling (MP) operations are used to design a UTL Network, that is capable of classifying multiple data types.

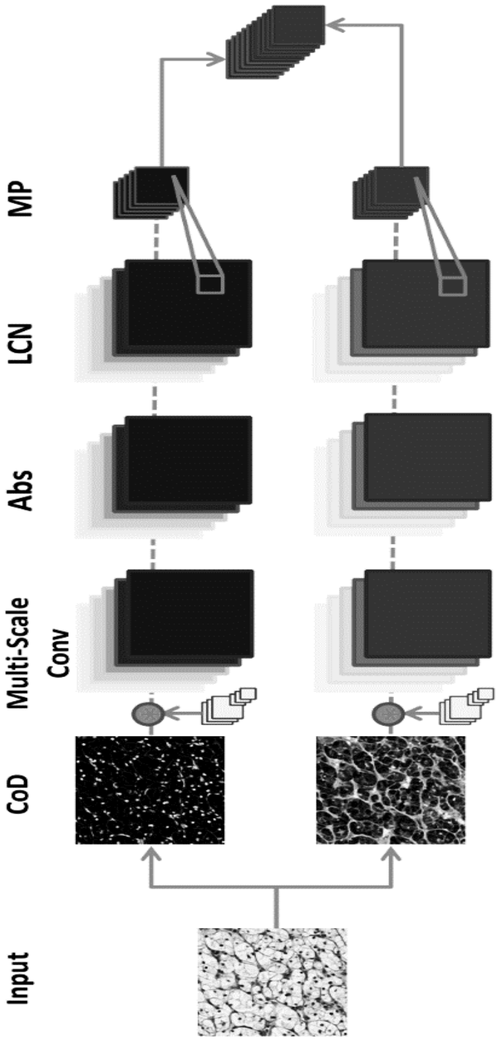

Fig 4. Design of the UTL MSCSC Model for efficient feature representations [5]

Due to use of these filters, the model showcases an accuracy of 93.42%, which is higher than Pseudo Multiple Scaled CSCSPM (PMS CSCSPM) (92.86%), Power Spectral Density with Stacked Predictive Sparse Coding (PSD2SPM) (91.85%), Sparse Morphometric Linear Spatial Pyramid Matching (SMLSPM) (92.35%), Sparse Coding (ScSPM) (79.58%), and Kernel SPM (KSPM) (85%) for the same dataset applications. But the model is highly complex, cannot detect irregularities in input datasets and requires large training & validation delays. To overcome these limitations, work in [6] proposes use of Implicit Irregularity Detection (IIRD) via use of unsupervised learning on temporal data patterns. The model uses a combination of Regression Analysis, Gaussian Distribution, Fuzzy Rule-base, and Probabilistic Modelling to estimate feature sets that can add periodicity to data samples. It initially constructs a Basic Regular Group (BRG) and performs its expansion via augmentation models. This augmentation is applied till periodicity is not achieved in the datasets, due to which the model is capable of achieving a linearly increasing accuracy 98.5%, that is higher than Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (94.1%), k Means (75.5%), and Hierarchical Clustering (HC) (78.9%) across multiple datasets. This model's performance can be further extended via use of Uncorrelated and Discriminative Feature Selection which is implemented via Constrained Spectral Analysis for efficient feature selection (DUCSAFS) as discussed in [7], which can be deployed under multiple heterogeneous datasets. The model initially explores low-redundant discriminative features, and avoids trivial solutions, which simplifies the optimisation process. Due to these characteristics, the model is applicable for multidimensional datasets with different classes and has minimum overheads. It is capable of achieving an accuracy of 89.5% under different applications, which is higher than Least Squares (LS) (64.5%), Nonnegative Discriminative Feature Selection (NDFS) (71.9%), Joint Embedding Learning and Sparse Regression (JELSR) (74.8%), Simultaneous Orthogonal basis Clustering Feature Selection (SOCFS) (83.5%), and Structure Optimal Graph Feature Selection (SOGFS) (89.1%) when evaluated under the same datasets. This model showcases superior performance, but doesn't incorporate explainable characteristics, which can be used to further improve it usability. To perform this task, work in [8] proposes use of SOM-based Explainable Clustering Methodology (SOM ECM), for generation of synthetic explanations. It calculates Unified Distance Matrix (U Matrix) for different component planes in order to solve segmentation, clustering, and classification tasks. The model is able to achieve an average accuracy of 79.5% under different applications.

Models that use Unsupervised & Nonlinear Adaptive Manifold Learning (UNAML) [9], Data Normalization for Neural Networks (DNNN) [10], Heterogeneous Coupling with Unsupervised Learning to represent Categorical datasets (HCUL) [11], and use of g Support Vector Machine (SVM) under unary and binary modes [12] are also discussed by researchers. The UNAML Model is capable of handling unsupervised datasets, while DNNN can be used to handle data from heterogenous sources with high efficiency and good classification performance. These models must be combined in order to design an integrated high-performance model that can cater to large-scale datasets. While HCUL showcases higher efficiency for representing data used in classification applications, which can be extended via use of SVM for achieving better accuracy, precision, recall and Area Under the Curve (AUC) levels. The UNAML model achieved an accuracy of 85.4%, while ANN showcased an accuracy of 73.9% under different applications. Upon similar evaluation, HCUL that uses multiple kernels was able to classify data with 91.5%, while SVM showcased an accuracy of 83.5% for MicroRNAs based classification applications. But these models do not use clustering techniques, which limits their data representation capabilities. To overcome this limitation, work in [13] proposes use of Hybrid Unsupervised Clustering (HUC) via integration of Sub-Space Clustering (SSC) & One Class Support Vector Machine (OCSVM) which assists in improving classification performance for multidimensional datasets. The HUC SSC OCSVM Model achieves an accuracy of 89.9%, which is higher than SSC with EA (86.2%), DBSCAN (85.9%), and k Means (83.4%) when averaged for different applications. This efficiency can be improved via integration of model enhancements in existing Neural Networks. Work in [14] proposes such a model, which uses Unsupervised Learning perceptron adopting phase change memory (PCM) synapses with Spike Timing Dependent Plasticity (STDP) & Neural Redundancy (NR) methods. These methods assist in integration of long-term memory availability, which improves classification performance when applied for multidimensional data applications. The PCM STDP NR model showcases an accuracy of 91.5%, which makes it useful for real-time deployments. This model must be validated on larger datasets, and can be further extended via use of Confidential Correspondence Consistency (CCC) as discussed in [15], which assists in high-efficiency augmentation of image sets to improve classification performance for data limited applications. The CCC model is depicted in figure 5, wherein Siamese CNN along with initial disparity, correspondence consistency, and positive sample propagation are used to achieve an accuracy of 91.2% under different datasets. This accuracy is higher than Content CNN (84.5%), and Global Context CNN (GC CNN) (89.5%) which makes it useful for a wide variety of real-time applications.

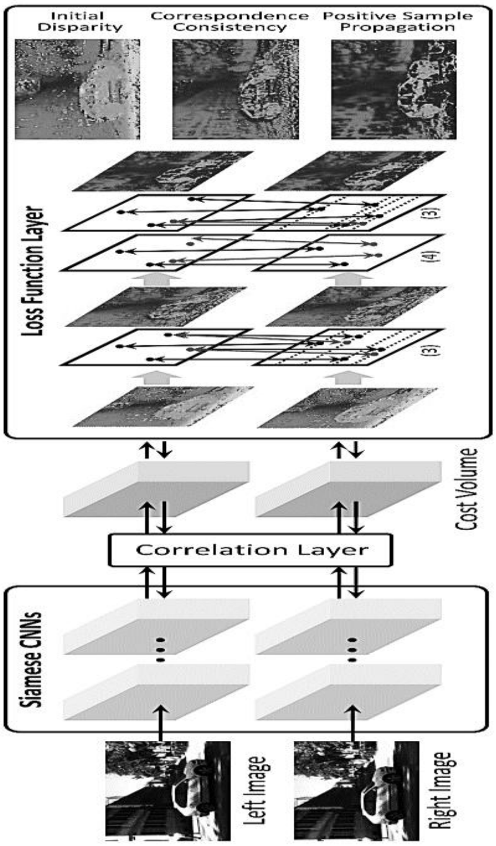

Fig 5. Design of CCC based CNN Model for low error & limited data capabilities-based classification applications [15]

The model must be tested on different datasets, and can be extended via use of low-cost & high-efficiency Q-Learning methods for incremental performance optimizations. Such models are discussed in [16, 17], which propose use of Multistage Method for Leveraging Order-Independent Transparency (MMLOIT), and combination of Event Shift with Histogram Shape (ESHS) which assists in continuously improving model performance via high-density feature extraction & selection techniques. The MMLOIT model is mainly used for data visualization, and can be deployed for a wide variety of applications, while the ESHS model is used for event analysis in terms of event chronology, periodic similarity and aperiodic similarity levels. A combination of both these models should be done to improve classification & representation performance. The MMLOIT model showcases an accuracy of 64.5%, while the ESHS model showcases an accuracy of 91.3% across different datasets. Extensions to these models are discussed in [18, 19] which propose use of Neural Network-Based Blind Equalization (NNBBE), and design of a new distance metric (NDM) which is based on dynamic attribute-level weights that are evaluated via use of frequency probabilities. These models assist in improving classification & pattern analysis performance for multiple applications. The NNBBE model is useful for training existing Neural Networks by integration of blind equalization which improves their accuracy performance. It showcases an accuracy of 96.5%, while NDM is able to achieve clustering accuracy of 91.4%, due to which, both models are useful for high-performance application deployments. These models must be validated on heterogeneous applications, which will assist in estimating its real-time performance. Such applications are discussed in [20, 21], which propose use of pattern analysis for text classification, and perceptual category learning based use cases. Text classification applications can use Variational Autoencoder Neural Networks (VANN) with Graph Regularization (GR), which assists in achieving an accuracy of 85.9% across different datasets. This model showcases better performance than Autoencoder (AE) (82.8%), Sparse AE (SAE) (78.5%), Stacked AE (STAE) (79.1%), Denoising AE (DAE) (85.9%), Restricted Boltzmann Machine (RBM) (72.3%), and Deep Belief Networks (DBNs) (73.5%) for the same datasets. While the perceptual category learning model initially converts all datasets into Gaussian distributions, and then mixes these distributions to design Online Mixture Estimation (OME), which assists in achieving an accuracy of 90.5% across different 1D datasets. To performance can be further improved via use of Extreme Learning Machines (ELMs) [22], Unsupervised Linear Discriminant Analysis (ULDA) [23], Support Vector Machine with Measure of Textual Lexical Diversity (SVM MTLD) [24], and CNN fused with Differentiable Feature Clustering (CNN DFC) [25], each of which assist in improving pattern analysis performance via feature augmentation process. ELMs are observed to be highly complex, and thus can be used under high-performance computing scenarios, while ULDA is capable of processing multidimensional data with high efficiency with low complexity, thus it is recommended that ULDA must be used for initial feature representations, while ELMs must be applied for feature learning process. SVMs also showcase good classification performance, and thus can be used to replace ELMs, but they cannot be used for applications with higher number of classes. The CNN DFC model is able to achieve both these characteristics due to use of Differentiable Feature Clustering, which assists in pre-processing the data before actual classification. Due to which, the CNN DFC model is highly useful for large-scale classification applications. The ELM model showcases an accuracy of 96.63%, which is higher than Laplacian Eigenmaps (LE) (91.5%), Spectral Clustering (SC) (89.2%), Deep Autoencoder (DA) (90.2%), and k Means (89.5%) for different datasets. While, the accuracy of ULDA is 86.5%, which is higher than LDA (85.2%), and Real Time LDA (RTLDA) (85.3%) across different multidimensional datasets. SVM showcases an accuracy of 83.1%, but has lower complexity than other models.

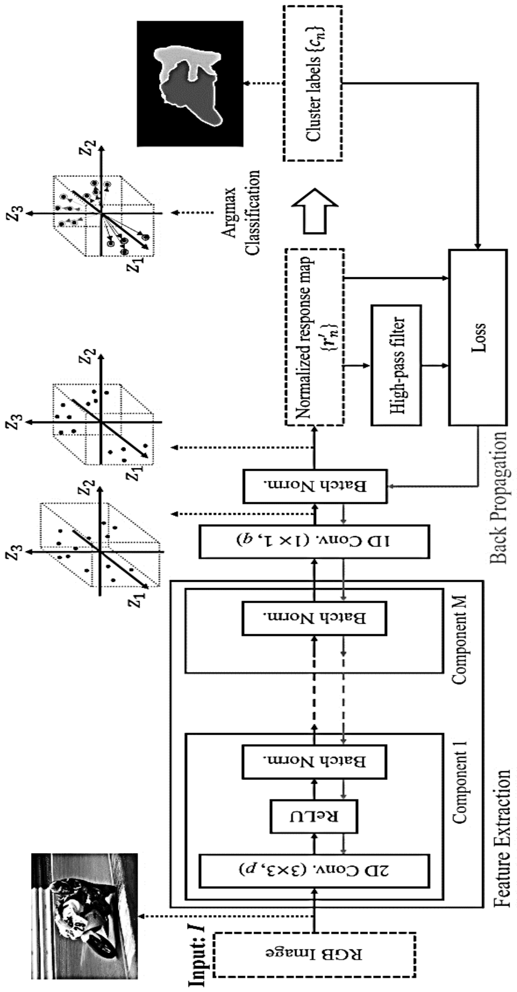

Fig 6. Integration of CNN with DFC for better signal processing performance

The CNN DFC model is depicted in figure 6, and outperforms all these models by achieving an accuracy of 95.4%, due to integration of Normalized Response Maps (NRMs), and filtering models for achieving better data processing capabilities.

These models are useful when applied to 2D or 3D datasets, but 1D datasets are used in a wide variety of practical applications. Work in [26, 27, 28] proposes use of SP theory based Neural Networks (SPNNs), customized 1D Reconfigurable Intelligent Surface Beamforming Neural Network (1D RISBNN), and Heterogeneous Unsupervised Domain Adaptation with Grassmann's Linear Monotonic Maps with Geodesic Flow Kernel (GLMM GFK), which assist in extraction of multidomain feature sets for highly efficient data representation purposes. These models utilize Fully Connected Neural Networks (FCNNs) for classifying & processing the extracted data into different application-specific categories. The SPNN Model is highly complex, but showcases an accuracy of 97.5%, which is better than 1D RISBNN that showcases an accuracy of 96.1 %, but can be used for multidimensional datasets. The GLMM GFK uses incremental feature updates, due to which it is capable of achieving accuracy between 86.1% to 96.4% for different applications. These models must be deployed for different applications, which will assist in estimating their real-time performance across multiple scenarios. Work in [29, 30] discusses such applications, wherein Kalman Filter with Pose CNN (KFP CNN), and Unsupervised Two-Path Neural Network (UTPNN) are applied to video processing, and high-density cell-based image processing applications. The KFP CNN model showcases an accuracy of 98.7%, while UTPNN achieves an accuracy of 85.6% under different datasets. The UTPNN model also proposes a custom Convolution Long-Short-Term Memory (Conv LSTM), which assist in extraction of multiple levels of features for improving data representation efficiency across different scenarios.

Pattern analysis models are also useful for solving issues that require remote & real-time monitoring for multiple inputs. Such applications, and their ML based solutions are proposed in [31, 32, 33], which discuss use of Prediction-based Proactive Drone Management (P2DM) with SVM, Variational Auto-Encoder (VAE) for Unsupervised Deep Spectrum Sensing, and Coupled CNN with Adaptive Response Function Learning (CCNN ARFL) for Unsupervised Hyperspectral Super Resolution applications. The P2DM Model is highly context sensitive, with low energy consumption and lower complexity, but achieves an accuracy of 73.5% under for drone sites. While the VAE Model showcases an accuracy of 93.5%, which makes it useful for spectrum sensing, but can be extended for other use cases. Similarly, the CCNN ARFL uses a combination of Low Resolution & High Resolution Hyper Spectral Imaging with Autoencoder (Lr & Hr HIS AE) as depicted in figure 7, which assists in achieving an accuracy of 91.5% under different dataset configurations. But these models are highly complex, and require large datasets for efficiency operations. To overcome this limitation, work in [34, 35, 36] proposes use of Two Stage CNN (TSNN), Unsupervised Deep Feature Learning (UDFL), and Instance-Based Learning with Q-Learning (IBQL) for data augmentation that can be used with low density datasets. These models integrate different information processing layers, which increases data representation efficiency for cross dataset applications. They also use incremental learning, which assists in continuous training set updates via correlation matching based feedbacks. Due to which the TSNN model showcases an accuracy of 89.1%, while UDFL achieves an accuracy of 94.8%, and while IBQL showcases an accuracy of 96.5% under different dimensional & different categorical datasets.

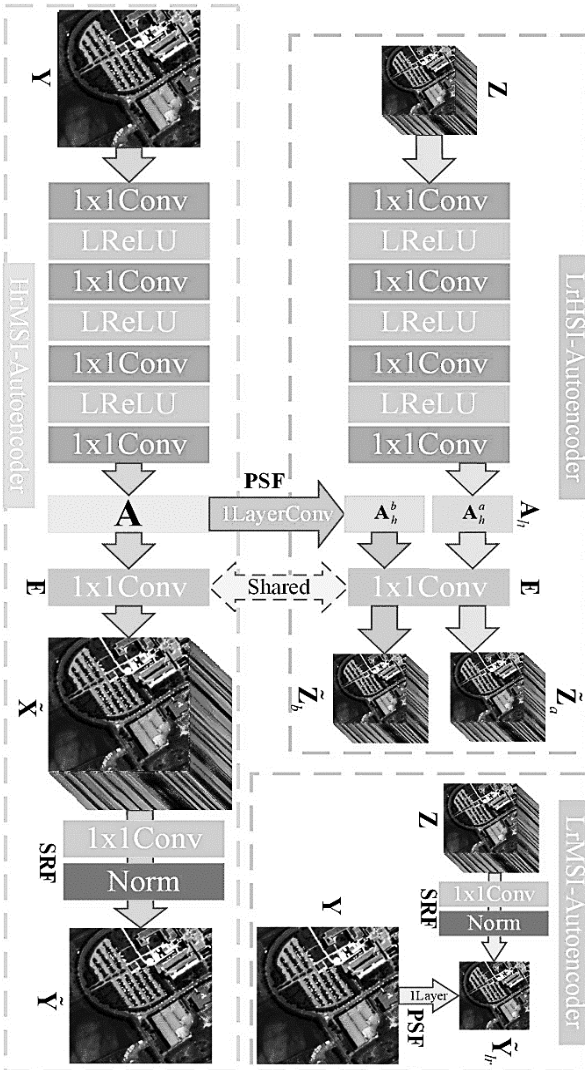

Fig 7. Design of CCNN ARFL Model for deploying high efficiency classification process

Extended deep learning models that use Masked Generative Adversarial Networks (M GAN) [37], Spiking Neural Network with Cross Modal Processing (SNN CMP) [38], and Selective Unsupervised Learning via Autoencoder with GAN (SUL AE GAN) [39], are discussed and deployed for large-scale applications. These models utilize application-specific feature processing in order to represent data with minimum overheads. The represented features are processed via augmented learning models which assists in improving their cross-dataset efficiency for different applications. The M GAN Model showcases an accuracy of 97.6%, while SNN CMP achieves can accuracy of 95.5%, while SUL AE GAN showcases an accuracy of 92.7% for multidimensional data applications. Extensions to these models are discussed in [40, 41, 42], which proposes use of different metrics like Response Time for Aberrant Response (RTA), kernel density maximum entropy (KDME), and discussion of different fusion & deep learning models which assist in improving processing performance for multiple application types. The RTA model showcases an accuracy of 83.4%, while KDME showcases an accuracy of 93.4% which makes them useful for real-time data processing applications. This performance can be improved via use of bioinspired models like Genetic Algorithm (GA) [43], Genetic Neural Network (GNN), [44] and Particle Swarm Optimization (PSO) based SVM [45] which assists in stochastically modelling different use cases for better learning performance. The GA Model assists in achieving an accuracy of 85.5%, while GNN showcases an accuracy of 91.4%, and PSO with SVM showcases an accuracy of 97.5% under different applications. These models have different use cases, but can be deployed for large-scale scenarios. To further analyze scalability of these models, they are compared in terms of accuracy, precision, recall, computational complexity, and scalability performance in the next section of this text. Based on this discussion, researchers will be able to identify best performing models, for their application-specific use cases.

3. Empirical evaluation and Comparison of reviewed models

From the literature survey it can be observed that existing learning models used for unsupervised analysis of existing cyber physical deployments have wide variety of applications. These models have performance variations based on context, deployment type, data type, and applicability. To facilitate model selection, this section compares the reviewed models in terms of their accuracy (A), precision (P), recall (R), computational complexity (C), and scalability (S) measures. These values are accumulated via pragmatic evaluation of these reference models. Out of these metrics, computational complexity & scalability do not have absolute values, thus, values of these metrics are evaluated in terms of fuzzy ranges of Low (L=1), Medium (M=2), High (H=3), and Very High (VH=4), which will assist readers to identify context-specific models for their deployments. These values can be observed from table 1 as follows,

Model	**A (%)**	**P (%)**	**R (%)**	**C**	**S**
IUD ANN [1]	96.95	74.24	75.60	H	M
CNN [1]	57.53	66.13	68.58	VH	M
DANN [1]	68.23	75.59	77.04	VH	H
iCNN [1]	72.62	84.01	84.83	VH	H
iDANN [1]	85.91	88.30	91.33	VH	H
TUMK ELM [2]	93.5	88.47	91.50	H	H
RMK KM [2]	85.5	89.37	89.04	M	L
LMK KM [2]	86.4	86.00	90.68	M	L
UCV ML [3]	96.2	85.03	86.69	H	M
XQDA [3]	75.4	81.47	83.21	H	M
CVD CA [3]	83.5	84.17	86.18	H	H
CAM EL [3]	85.5	82.93	85.00	H	M
ANN [4]	83.5	79.57	81.05	H	H
HMM [4]	79.8	73.23	77.84	VH	M
PGM [4]	75.4	75.13	74.36	H	M
NCDM [4]	64.5	74.97	79.38	H	H
SOKM [4]	85.5	84.61	85.15	H	L
SNE [4]	74.9	87.06	89.25	M	L
UTL MSC SC [5]	93.42	92.71	95.22	H	H
PMS CSC SPM [5]	92.86	92.35	93.59	H	H
PSD2 SPM [5]	91.85	87.93	91.74	H	L
SML SPM [5]	92.35	85.64	88.53	H	L
Sc SPM [5]	79.58	87.69	88.41	H	M
KSPM [5]	85	92.53	93.69	H	L
IIRD [6]	98.5	89.37	93.54	VH	H
DB SCAN [6]	94.1	82.83	85.57	H	H
k Means [6]	75.5	81.30	80.34	M	L
HC [6]	78.9	77.63	82.39	L	M
DUC SAFS [7]	89.5	75.30	76.85	H	H
LS [7]	64.5	70.40	72.70	H	H
NDFS [7]	71.9	76.73	78.44	H	H
JELSR [7]	74.8	82.47	83.28	H	H
SOCFS [7]	83.5	84.03	87.51	H	H
SOGFS [7]	89.1	84.67	85.35	H	H

SOM ECM [8]	79.5	79.60	84.13	VH	H
UN AML [9]	85.4	83.60	83.56	VH	M
DNNN [10]	73.9	82.97	86.32	H	M
HCUL [11]	91.5	88.30	89.70	VH	H
SVM [12]	83.5	86.53	89.04	L	M
HUC OC SVM [13]	89.9	87.33	89.38	VH	H
SSC EA [13]	86.2	85.17	88.26	H	H
DB SCAN [13]	85.9	86.93	88.44	H	H
k Means [13]	83.4	88.70	90.43	M	L
STDP [14]	91.5	89.07	92.35	H	M
CCC [15]	91.2	88.40	88.10	VH	H
Content CNN [15]	84.5	79.50	85.97	VH	VH
GC CNN [15]	89.5	81.77	82.02	VH	VH
MML OIT [16]	64.5	84.10	85.38	H	H
ESHS [17]	91.3	93.07	95.42	H	H
NN BBE [18]	96.5	91.27	93.81	VH	H
NDM [19]	91.4	86.70	88.82	VH	H

VANN GR [20]	85.9	82.40	84.93	VH	H
AE [20]	82.8	80.13	82.72	VH	VH
SAE [20]	78.5	81.17	81.50	VH	VH
STAE [20]	79.1	79.10	82.39	VH	VH
DAE [20]	85.9	77.23	80.56	VH	VH
RBM [20]	72.3	78.77	79.83	VH	VH
DBNs [20]	73.5	86.77	88.09	VH	VH
OME [21]	90.5	92.77	95.36	H	H
ELMs [22]	96.3	92.33	94.98	VH	VH
LE [22]	91.5	90.30	92.47	H	H
SC [22]	89.2	89.63	91.74	H	H
DA [22]	90.2	88.73	91.15	H	VH
k Means [22]	89.5	87.07	89.42	M	L
ULDA [23]	86.5	85.67	87.67	VH	H
LDA [23]	85.2	84.53	87.94	H	H
RT LDA [23]	85.3	87.93	89.32	H	H
SVM MTLD [24]	83.1	92.00	94.06	H	H
CNN DFC [25]	95.4	96.33	98.85	VH	VH
SPNN [26]	97.5	96.30	99.13	VH	H
1D RIS BNN [27]	96.1	96.70	97.77	VH	H

GLMM GFK [28]	95.3	93.20	95.68	VH	H
KFP CNN [29]	98.7	85.93	90.88	VH	VH
UTP NN [30]	85.6	84.20	84.48	H	H
P2DM SVM [31]	73.5	86.17	88.34	H	H
VAE [32]	93.5	91.37	94.40	VH	H
CCNN ARFL [33]	91.5	91.80	93.81	VH	H
TSNN [34]	89.1	93.47	95.81	VH	VH
UDFL [35]	94.8	96.30	98.50	H	H
IBQL [36]	96.5	96.53	98.95	VH	VH
M GAN [37]	97.6	95.27	97.15	VH	VH
SNN CMP [38]	95.5	90.53	94.50	VH	H
SUL AE GAN [39]	92.7	89.83	90.61	VH	VH
RTA [40]	83.4	87.43	90.85	H	H
KDME [41]	93.4	90.10	92.43	H	H
GA [43]	85.5	91.47	92.80	L	H
GNN [44]	91.4	93.57	96.47	H	VH
PSO [45]	97.5	93.75	72.58	H	H

Table 1. Statistical evaluation of different unsupervised learning models

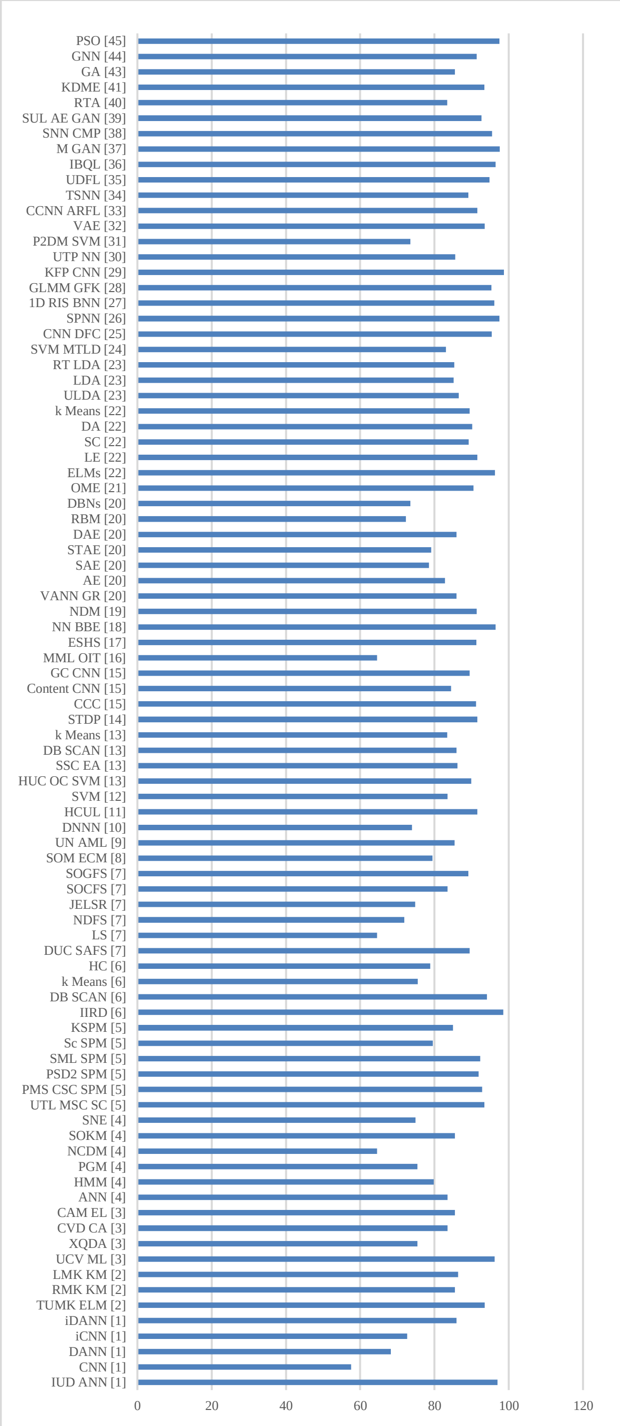

Fig 8. Accuracy of different models

Based on this evaluation and figure 8 it can be observed that KFP CNN [29], IIRD [6], M GAN [37], SPNN [26], PSO [45], IUD ANN [1], NN BBE [18], IBQL [36], ELMs [22], UCV ML [3], and 1D RIS BNN [27] have highest accuracy, thus they can be used for high-accuracy unsupervised learning application deployments.

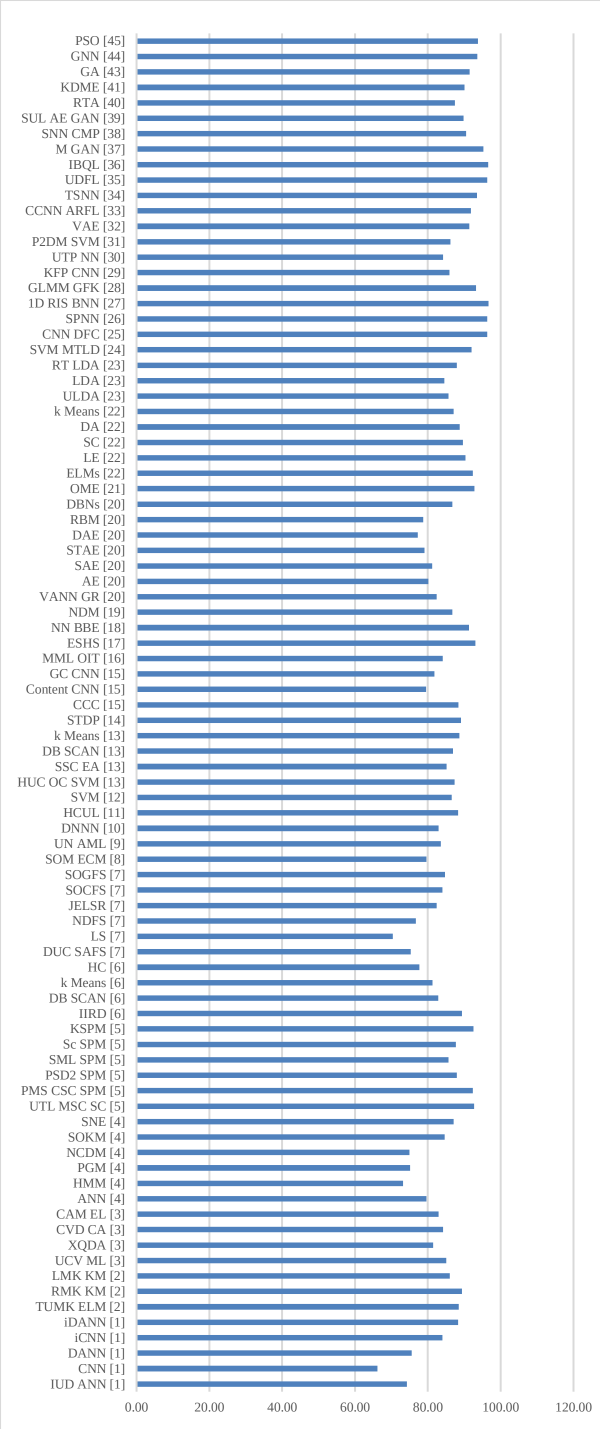

Fig 9. Precision of different models

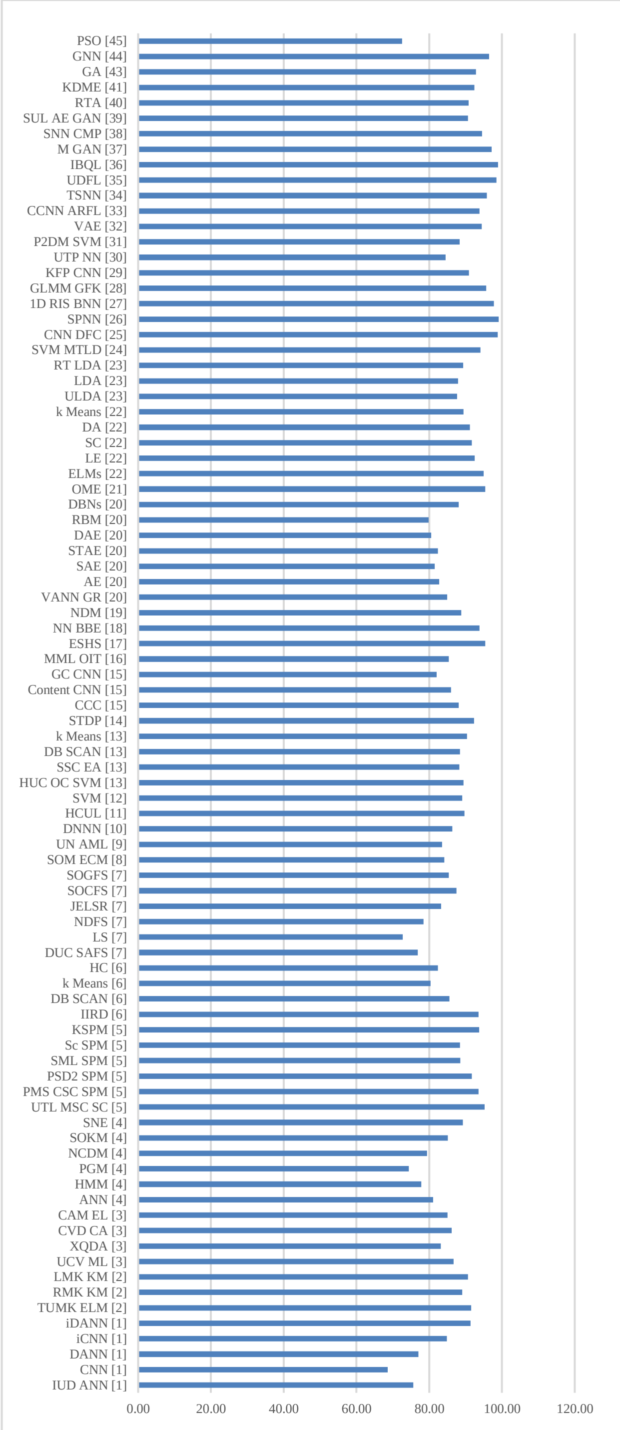

Fig 10. Recall of different models

Similarly, from table 1 and figure 9, it can be observed that 1D RIS BNN [27], IBQL [36], CNN DFC [25], SPNN [26], UDFL [35], M GAN [37], PSO [45], GNN [44], and TSNN [34] have better precision, which makes them useful for applications that require consistent performance across different evaluations.

Similarly, from table 1 and figure 10, it can be observed that SPNN [26], IBQL [36], CNN DFC [25], UDFL [35], 1D RIS BNN [27], M GAN [37], GNN [44], TSNN [34], and GLMM GFK [28] have better recall, which makes them useful for applications that require low error performance across different evaluations.

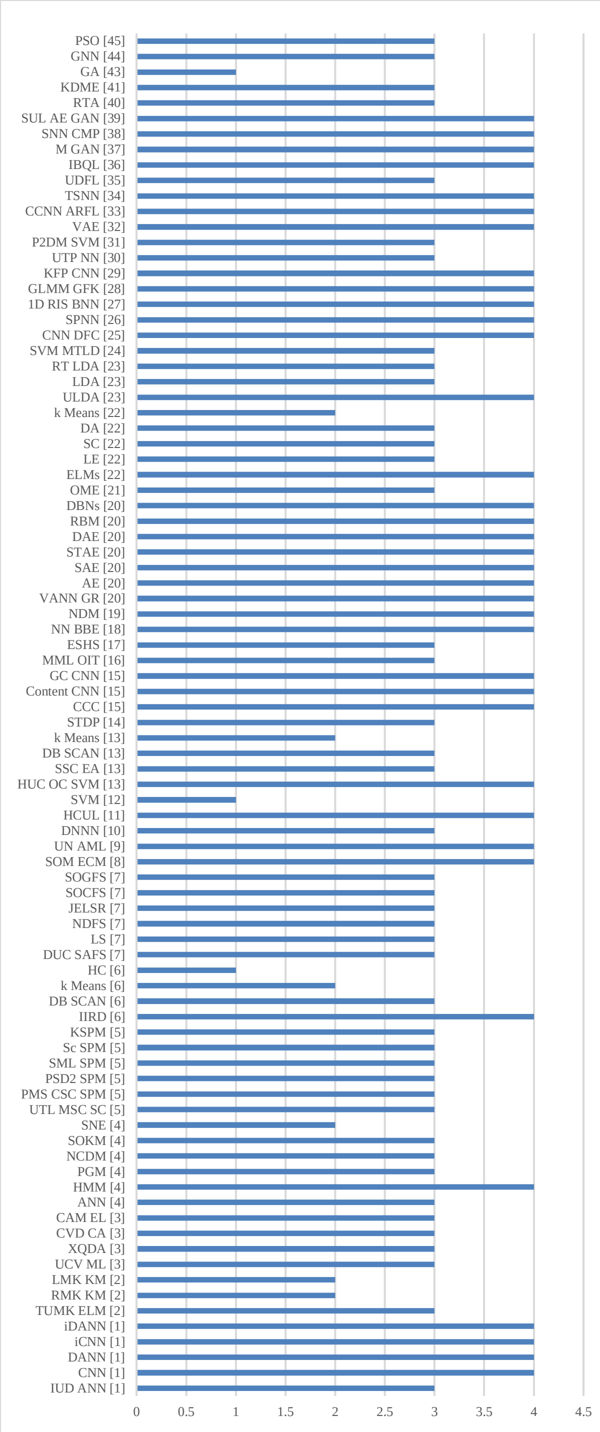

Fig 11. Computational Complexity of different models

Similarly, from table 1 and figure 11, it can be observed that HC [6], SVM [12], GA [43], RMK KM [2], LMK KM [2], SNE [4], and k Means [6] have lower complexity, which makes them useful for high-speed applications across different evaluations.

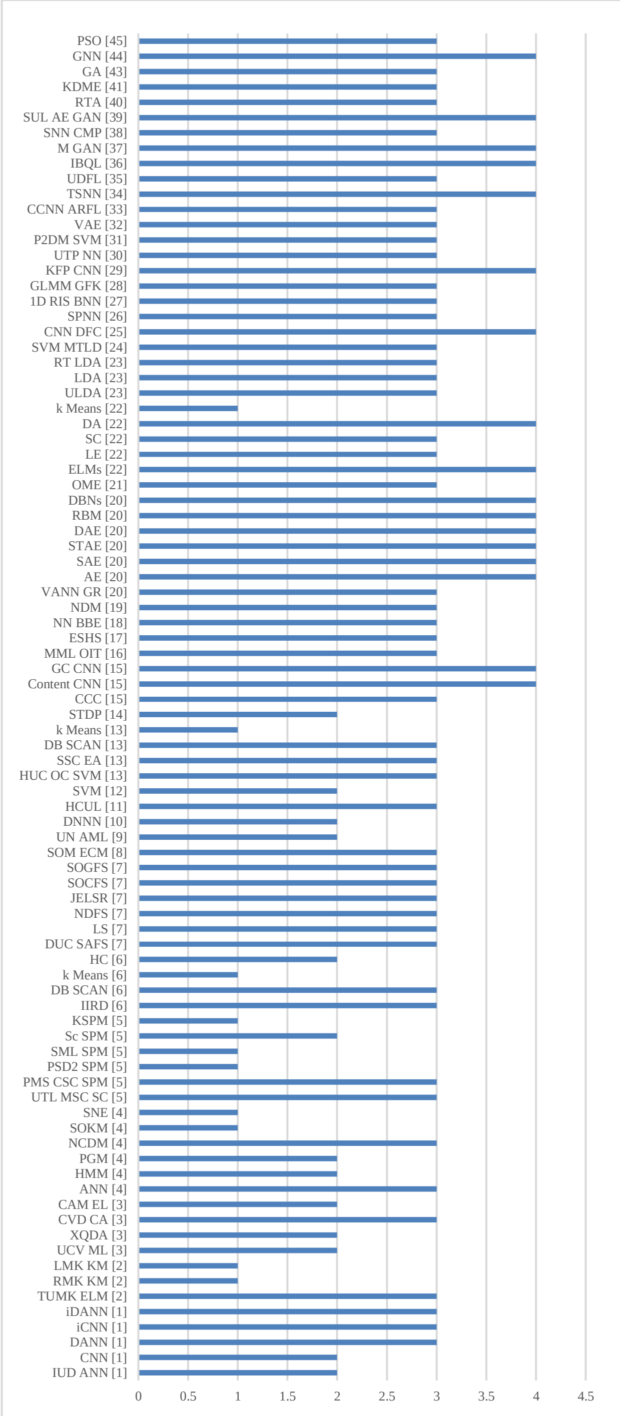

Fig 12. Scalability of different models

Similarly, from table 1 and figure 12, it can be observed that Content CNN [15], GC CNN [15], AE [20], SAE [20], STAE [20], DAE [20], RBM [20], DBNs [20], and ELMs [22] have higher scalability, which makes them useful for large-scale applications.

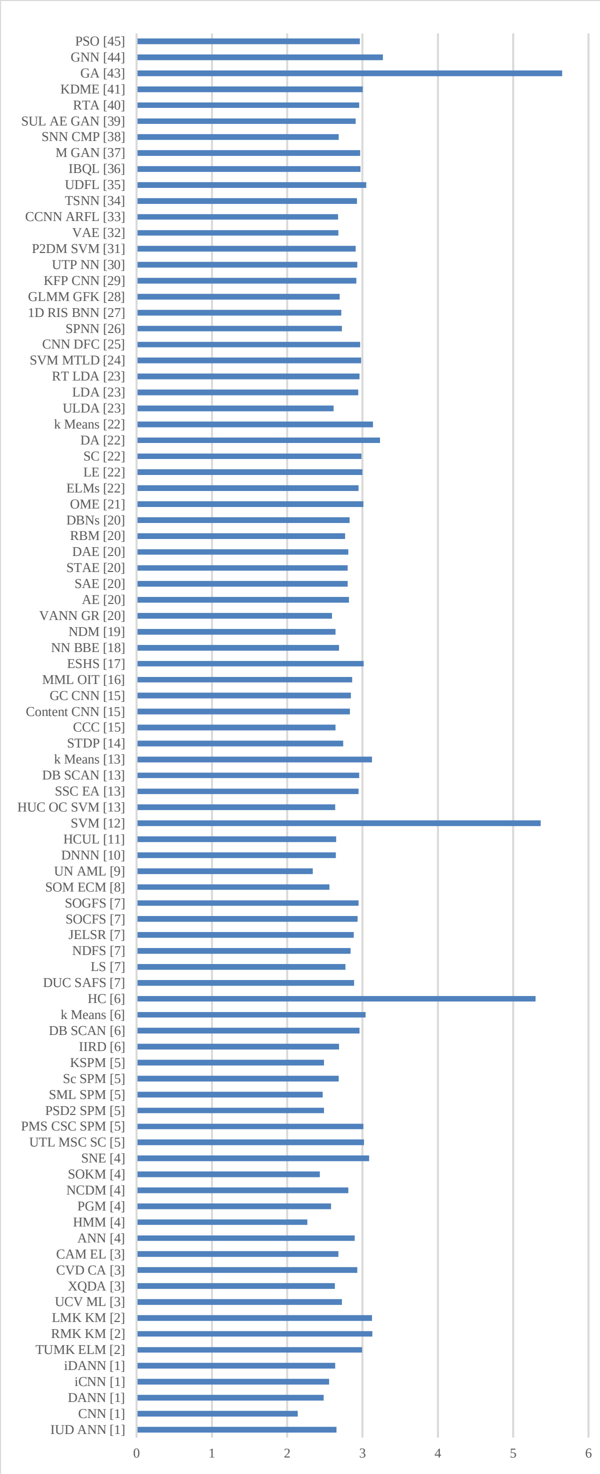

Fig 13. NRM of different models

To further assist in improving model selection process, a Novel Rank Metric (NRM) is evaluated via equation 1, which assists in combining accuracy, precision, recall, complexity and scalability metrics.

$$NRM = \frac{P + R + A}{300} + \frac{4}{C} + \frac{S}{4} \dots (1)$$

Based on this evaluation and figure 13 it was observed that GA [43], SVM [12], HC [6], GNN [44], DA [22], k Means [22], RMK KM [2], LMK KM [2], SNE [4], UDFL [35], UTL MSC SC [5], ESHS [17], PMS CSC SPM [5], OME [21], and KDME [41] have better overall performance, which makes them useful for high accuracy, high precision, high recall, low complexity and highly scalable application deployments. Thus, these models must be used when designing unsupervised learning applications for optimum performance under different use cases.

4. Conclusion

This text extensively compares different unsupervised learning models in terms of their context-specific nuances, application-based advantages, functional limitations, and recommends various future enhancements, which will assist in improving its real-time performance. From this evaluation it was observed that existing models use ML methods along with bioinspired techniques for continuous performance optimizations, which assists in improving their real-time performance under different applications. It was also observed that effective feature representation along with optimized distance metrics have better performance when compared with their counterparts. This evaluation concludes that KFP CNN, IIRD, M GAN, SPNN, PSO, IUD ANN, NN BBE, IBQL, ELMs, UCV ML, and D RIS BNN have highest accuracy, D RIS BNN, IBQL, CNN DFC, SPNN, UDFL, M GAN, PSO, GNN, and TSNN have better precision, while, SPNN, IBQL, CNN DFC, UDFL, D RIS BNN, M GAN, GNN, TSNN, and GLMM GFK have better recall, which makes them useful for high accuracy applications that require low error performance across different evaluations. It was also observed that HC, SVM, GA, RMK KM, LMK KM, SNE, and k Means have lower complexity, while Content CNN, GC CNN, AE, SAE, STAE, DAE, RBM, DBNs, and ELMs have higher scalability, which makes them useful for high-speed & large-scale applications. These metrics were combined and a Novel Rank Metric was evaluated, which recommends that GA, SVM, HC, GNN, DA, k Means, RMK KM, LMK KM, SNE, UDFL, UTL MSC SC, ESHS, PMS CSC SPM, OME, and KDME have better overall performance, which makes them useful for high accuracy, high precision, high recall, low complexity and highly scalable application deployments. Thus, these models must be used when designing unsupervised learning applications for optimum performance under different use cases. In future, it is recommended that researchers must use a combination of these models which will assist them in improving their real time performance under different use cases. Furthermore, validation of these models must be done for large-scale applications, which will assist them in recognizing their scalability performance for multiple application scenarios.

5. References

[1] A. -J. Gallego, J. Calvo-Zaragoza and R. B. Fisher, "Incremental Unsupervised Domain-Adversarial Training of Neural Networks," in IEEE Transactions on Neural Networks and Learning Systems, vol. 32, no. 11, pp. 4864-4878, Nov. 2021, doi: 10.1109/TNNLS.2020.3025954.

[2] L. Xiang, G. Zhao, Q. Li, W. Hao and F. Li, "TUMK-ELM: A Fast Unsupervised Heterogeneous Data Learning Approach," in IEEE Access, vol. 6, pp. 35305-35315, 2018, doi: 10.1109/ACCESS.2018.2847037.

[3] Y. Feng, Y. Yuan and X. Lu, "Person Reidentification via Unsupervised Cross-View Metric Learning," in IEEE Transactions on Cybernetics, vol. 51, no. 4, pp. 1849-1859, April 2021, doi: 10.1109/TCYB.2019.2909480.

[4] M. Usama et al., "Unsupervised Machine Learning for Networking: Techniques, Applications and Research Challenges," in IEEE Access, vol. 7, pp. 65579-65615, 2019, doi: 10.1109/ACCESS.2019.2916648.

[5] H. Chang, J. Han, C. Zhong, A. M. Snijders and J. -H. Mao, "Unsupervised Transfer Learning via Multi-Scale Convolutional Sparse Coding for Biomedical Applications," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 40, no. 5, pp. 1182-1194, 1 May 2018, doi: 10.1109/TPAMI.2017.2656884.

[6] C. Shang, C. -Y. Chang, G. Chen, S. Zhao and J. Lin, "Implicit Irregularity Detection Using Unsupervised Learning on Daily Behaviors," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 1, pp. 131-143, Jan. 2020, doi: 10.1109/JBHI.2019.2896976.

[7] X. Li, H. Zhang, R. Zhang and F. Nie, "Discriminative and Uncorrelated Feature Selection With Constrained Spectral Analysis in Unsupervised Learning," in IEEE Transactions on Image Processing, vol. 29, pp. 2139-2149, 2020, doi: 10.1109/TIP.2019.2947776.

[8] C. S. Wickramasinghe, K. Amarasinghe, D. L. Marino, C. Rieger and M. Manic, "Explainable Unsupervised Machine Learning for Cyber-Physical Systems," in IEEE Access, vol. 9, pp. 131824-131843, 2021, doi: 10.1109/ACCESS.2021.3112397.

[9] J. Gao, F. Li, B. Wang and H. Liang, "Unsupervised nonlinear adaptive manifold learning for global and local information," in Tsinghua Science and Technology, vol. 26, no. 2, pp. 163-171, April 2021, doi: 10.26599/TST.2019.9010049.

[10] G. Chakraborty and B. Chakraborty, "A novel normalization technique for unsupervised learning in ANN," in IEEE Transactions on Neural Networks, vol. 11, no. 1, pp. 253-257, Jan. 2000, doi: 10.1109/72.822529.

[11] C. Zhu, L. Cao and J. Yin, "Unsupervised Heterogeneous Coupling Learning for Categorical Representation," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 1, pp. 533-549, 1 Jan. 2022, doi: 10.1109/TPAMI.2020.3010953.

[12] Sedaghat, Nafiseh & Fathy, Mahmood & Modarressi, Mohammad H. & Shojaie, Ali. (2017). Combination of Supervised and Unsupervised Approaches for miRNA Target Prediction. IEEE/ACM Transactions on Computational Biology and Bioinformatics. PP. 1-1. 10.1109/TCBB.2017.2727042.

[13] G. Pu, L. Wang, J. Shen and F. Dong, "A hybrid unsupervised clustering-based anomaly detection method," in Tsinghua Science and Technology, vol. 26, no. 2, pp. 146-153, April 2021, doi: 10.26599/TST.2019.9010051.

[14] I. Muñoz-Martín, S. Bianchi, G. Pedretti, O. Melnic, S. Ambrogio and D. Ielmini, "Unsupervised Learning to Overcome Catastrophic Forgetting in Neural Networks," in IEEE Journal on Exploratory Solid-State Computational Devices and Circuits, vol. 5, no. 1, pp. 58-66, June 2019, doi: 10.1109/JXCDC.2019.2911135.

[15] S. Joung, S. Kim, K. Park and K. Sohn, "Unsupervised Stereo Matching Using Confidential Correspondence Consistency," in IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 5, pp. 2190-2203, May 2020, doi: 10.1109/TITS.2019.2917538.

[16] Fuchs, Franz & Hjelmervik, Jon. (2014). Interactive Isogeometric Volume Visualization with Pixel-Accurate Geometry. IEEE Transactions on Visualization and Computer Graphics. 10.1109/TVCG.2015.2430337.

[17] C. Shang, C. -Y. Chang, G. Chen, S. Zhao and H. Chen, "BIA: Behavior Identification Algorithm

Using Unsupervised Learning Based on Sensor Data for Home Elderly," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 6, pp. 1589-1600, June 2020, doi: 10.1109/JBHI.2019.2943391.

[18] T. Liao, L. Xue, W. Hu and L. Yi, "Unsupervised Learning for Neural Network-Based Blind Equalization," in IEEE Photonics Technology Letters, vol. 32, no. 10, pp. 569-572, 15 May15, 2020, doi: 10.1109/LPT.2020.2985307.

[19] H. Jia, Y. -m. Cheung and J. Liu, "A New Distance Metric for Unsupervised Learning of Categorical Data," in IEEE Transactions on Neural Networks and Learning Systems, vol. 27, no. 5, pp. 1065-1079, May 2016, doi: 10.1109/TNNLS.2015.2436432.

[20] S. Wang, J. Cai, Q. Lin and W. Guo, "An Overview of Unsupervised Deep Feature Representation for Text Categorization," in IEEE Transactions on Computational Social Systems, vol. 6, no. 3, pp. 504-517, June 2019, doi: 10.1109/TCSS.2019.2910599.

[21] Lake, Brenden & Vallabha, Gautam & Mcclelland, James. (2009). Modeling Unsupervised Perceptual Category Learning. IEEE T. Autonomous Mental Development. 1. 35-43. 10.1109/DEVLRN.2008.4640800.

[22] G. Huang, S. Song, J. N. D. Gupta and C. Wu, "Semi-Supervised and Unsupervised Extreme Learning Machines," in IEEE Transactions on Cybernetics, vol. 44, no. 12, pp. 2405-2417, Dec. 2014, doi: 10.1109/TCYB.2014.2307349.

[23] F. Wang, Q. Wang, F. Nie, Z. Li, W. Yu and R. Wang, "Unsupervised Linear Discriminant Analysis for Jointly Clustering and Subspace Learning," in IEEE Transactions on Knowledge and Data Engineering, vol. 33, no. 3, pp. 1276-1290, 1 March 2021, doi: 10.1109/TKDE.2019.2939524.

[24] Michael Ustaszewski (2021) Towards a machine learning approach to the analysis of indirect translation, Translation Studies, 14:3, 313-331, DOI: 10.1080/14781700.2021.1894226

[25] Kim, Wonjik & Kanezaki, Asako & Masayuki, Tanaka. (2020). Unsupervised Learning of Image Segmentation Based on Differentiable Feature Clustering. IEEE Transactions on Image Processing. 29. 1-1. 10.1109/TIP.2020.3011269.

[26] J. G. Wolff, "Autonomous Robots and the SP Theory of Intelligence," in IEEE Access, vol. 2, pp. 1629-1651, 2014, doi: 10.1109/ACCESS.2014.2382753.

[27] J. Gao, C. Zhong, X. Chen, H. Lin and Z. Zhang, "Unsupervised Learning for Passive Beamforming," in IEEE Communications Letters, vol. 24, no. 5, pp. 1052-1056, May 2020, doi: 10.1109/LCOMM.2020.2965532.

[28] F. Liu, G. Zhang and J. Lu, "Heterogeneous Domain Adaptation: An Unsupervised Approach," in IEEE Transactions on Neural Networks and Learning Systems, vol. 31, no. 12, pp. 5588-5602, Dec. 2020, doi: 10.1109/TNNLS.2020.2973293.

[29] Y. Wang and Y. Xu, "Unsupervised Learning of Accurate Camera Pose and Depth From Video Sequences With Kalman Filter," in IEEE Access, vol. 7, pp. 32796-32804, 2019, doi: 10.1109/ACCESS.2019.2903871.

[30] Phan, Ha & Kumar, Ashnil & Fulham, Michael & Kim, Jinman. (2019). Unsupervised Two-Path Neural Network for Cell Event Detection and Classification Using Spatiotemporal Patterns. IEEE Transactions on Medical Imaging. 38. 1477-1487. 10.1109/TMI.2018.2885572.

[31] S. -H. Cheng, Y. -T. Shih and K. -C. Chang, "Proactive Power Control and Position Deployment for Drone Small Cells: Joint Supervised and Unsupervised Learning," in IEEE Access, vol. 9, pp. 126735-126747, 2021, doi: 10.1109/ACCESS.2021.3111964.

[32] J. Xie, J. Fang, C. Liu and L. Yang, "Unsupervised Deep Spectrum Sensing: A Variational Auto-Encoder Based Approach," in IEEE Transactions on Vehicular Technology, vol. 69, no. 5, pp. 5307-5319, May 2020, doi: 10.1109/TVT.2020.2982203.

[33] K. Zheng et al., "Coupled Convolutional Neural Network With Adaptive Response Function Learning for Unsupervised Hyperspectral Super Resolution," in IEEE Transactions on Geoscience and Remote Sensing, vol. 59, no. 3, pp. 2487-2502, March 2021, doi: 10.1109/TGRS.2020.3006534.

[34] H. Song, M. Zhang, J. Gao and C. Zhong, "Unsupervised Learning-Based Joint Active and Passive Beamforming Design for Reconfigurable Intelligent Surfaces Aided Wireless Networks," in IEEE Communications Letters, vol. 25, no. 3, pp. 892-896, March 2021, doi: 10.1109/LCOMM.2020.3041510.

[35] Z. Gong, P. Zhong and W. Hu, "Unsupervised Deep Feature Learning With Iteratively Refined Pseudo Classes for Scene Representation," in

IEEE Access, vol. 7, pp. 94779-94792, 2019, doi: 10.1109/ACCESS.2019.2928328.
[36] A. Gupta, P. P. Roy and V. Dutt, "Evaluation of Instance-Based Learning and Q-Learning Algorithms in Dynamic Environments," in IEEE Access, vol. 9, pp. 138775-138790, 2021, doi: 10.1109/ACCESS.2021.3117855.
[37] C. Zhao, G. G. Yen, Q. Sun, C. Zhang and Y. Tang, "Masked GAN for Unsupervised Depth and Pose Prediction With Scale Consistency," in IEEE Transactions on Neural Networks and Learning Systems, vol. 32, no. 12, pp. 5392-5403, Dec. 2021, doi: 10.1109/TNNLS.2020.3044181.
[38] N. Rathi and K. Roy, "STDP Based Unsupervised Multimodal Learning With Cross-Modal Processing in Spiking Neural Networks," in IEEE Transactions on Emerging Topics in Computational Intelligence, vol. 5, no. 1, pp. 143-153, Feb. 2021, doi: 10.1109/TETCI.2018.2872014.
[39] J. H. Seong and D. H. Seo, "Selective Unsupervised Learning-Based Wi-Fi Fingerprint System Using Autoencoder and GAN," in IEEE Internet of Things Journal, vol. 7, no. 3, pp. 1898-1909, March 2020, doi: 10.1109/JIOT.2019.2956986.
[40] Pan, Y. and Wollack, J.A. (2021), An Unsupervised-Learning-Based Approach to Compromised Items Detection. Journal of Educational Measurement, 58: 413-433. https://doi.org/10.1111/jedm.12299
[41] Eltouny, KA, Liang, X. Bayesian-optimized unsupervised learning approach for structural damage detection. *Comput Aided Civ Inf*. 2021; 36: 1249– 1269. https://doi.org/10.1111/mice.12680
[42] Jo, Taeho. (2021). Machine Learning Foundations: Supervised, Unsupervised, and Advanced Learning. 10.1007/978-3-030-65900-4.
[43] Xueli Wang, Jingjuan Gao, "Optimization Model of Logistics Task Allocation Based on Genetic Algorithm", *Security and Communication Networks*, vol. 2022, Article ID 5950876, 13 pages, 2022. https://doi.org/10.1155/2022/5950876
[44] JingJing Zhao, "Risk Assessment Method of Agricultural Management Investment Based on Genetic Neural Network", *Security and Communication Networks*, vol. 2022, Article ID 2373363, 10 pages, 2022. https://doi.org/10.1155/2022/2373363
[45] Zhenglei Zhang, "The Application of PSO-SVM Algorithm in the Evaluation System of Sports Competition Events", *Security and Communication Networks*, vol. 2022, Article ID 6865425, 8 pages, 2022. https://doi.org/10.1155/2022/6865425