Industry 4.0 for SMEs: Exploring Operationalization Barriers and Smart Manufacturing with UKSSL and APO Optimization

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***Abstract*—The research aimed to find out why SMEs have a hard time adopting smart manufacturing, what makes smart manufacturing operational, and if only large companies can afford to take advantage of technological opportunities. It used a knowledge-based semi-supervised framework named Unsupervised Knowledge-based Multi-Layer Perceptron (UKMLP), which has two parts: a contrast learning algorithm that takes the unlabeled dataset and uses it to extract feature representations, and a UKMLP that uses that representation to classify the input data using the limited labelled dataset. Next, an artificial protozoa optimizer (APO) makes the necessary adjustments. This research is based on the hypothesis that large companies may be able to exploit Small and Medium-sized Enterprises (SMEs) to their detriment in cyber-physical production systems, thus cutting them out of the market. Secondary data analysis, which involved evaluating and analyzing data that had already been collected, was crucial in accomplishing the research purpose. Since big companies are usually the center of attention in these discussions, the necessity to delve into this subject stems from the reality that SMEs have a higher research need. The results confirmed the importance of Industry 4.00 in industrial production, particularly with regard to the smart process planning offered by algorithms for virtual simulation and deep learning. The report also covered the various connection choices available to SMEs in order to improve business productivity through the use of autonomous robotic technology and machine intelligence. This research suggests that a substantial value-added opportunity may lie in the way Industry 4.0 interacts with the economic organization of companies.**

Keywords*—European small and medium-sized enterprises; artificial protozoa optimizer; knowledge-based semi-supervised framework; contrastive learning algorithm; smart manufacturing

I. Introduction

Because data and the interactions among data cases reveal insights into software and service quality, as well as the dynamics of software creation and evolution, data plays a crucial role in contemporary software development [1-2]. There is a treasure trove of information regarding the development and evolution of a project in Software Engineering (SE) data, including code bases, changes, mailing lists, forum discussion, and bug/issue reports [3]. Automated SE methods and tools have come a long way since their inception, but most of them have concentrated on automating the creation, storage, and management of data that is specific to a single SE task, rather than helping with human experience-based decision-making or increasing productivity across all SE tasks [4]. The aforementioned methodologies and tools for software project decision-making, particularly in the face of uncertainty and that are unable to disclose the hidden linkages among different types of data or the data's deep semantics [5]. Thanks to the advancements in Machine Learning (ML) and Deep Learning (DL) algorithms, ML/DL models can now be trained to systematically evaluate and integrate data from big data software repositories, as to find patterns and new information clusters [6-7]. This paves the way for more thorough and organized information and decision-making frameworks [9] by improving comprehension of the data's deep semantics and interconnections via the use of statistical and probabilistic procedures [8]. Insightful and useful information regarding software systems and projects can be automatically uncovered by ML/DL approaches by analyzing and crosslinking the abundant data found in software repositories, something that cannot be accomplished just by practitioners' intuition and expertise [10]. The use of ML approaches in the automation of SE processes has also been driven by the exponential growth in the volume and difficulty of SE data.

The widespread use of ML/DL for data representation and analysis stems from the fact that many SE problems can be expressed as data analysis (learning) tasks [11]. These tasks include classification, ranking, regression, and generation, where the aims are to classify data instances into predefined categories, induce rankings over data instances, assign real values to data instances, and generate (usually brief) natural language descriptions as outputs [12–13]. As an example, it is natural to cast binary defect prediction as a classification job. This task involves predicting whether new instances of code regions (such as files, modifications, and methods) include faults. Ranking tasks can be applied to software crowdsourcing activities such as code search, defect localization, bug assignment, pull requests, requirements, reports, test case prioritization, and recommendations [14]. Software engineering (SE) researchers also use continuous data with regression models to approximation (1) software development effort [15], (2) software defect count and bug fixing time, (3) configurable software performance, (4) energy consumption, and (5) software reliability, a conditional probability problem. As a last step, certain activities have been reformed as generation tasks. One of them is code summarization, which involves providing a high-level, plain language description of the code. Another is the development of code artifacts, such as code comments.

To get the feature map out of datasets without labels, to use a contrastive learning model here [30]. In the next step, to build a model besides train it with a small dataset of labels. When tested on several classification datasets, the proposed framework UKSSL outperforms other state-of-the-art algorithms while utilizing a smaller dataset. In order to enhance the classification accuracy, the study work employs the APO model to refine the parameters of the proposed model. Here is a rundown of the remaining research: Section II lists relevant literature; Section III gives a brief overview of the proposed technique; Section IV analyses the results; and Section V attractions conclusions.

II. Related Work

Data privacy and algorithmic bias are two of the ethical issues that Kedi et al., [17] has explored in addition to the technical difficulties of applying machine learning, which include algorithm complexity, system integration, and data quality. To also talk about the limits that are unique to SMEs, such as limited resources and a lack of technical knowledge. The future is bright for new technologies like reinforcement learning and deep learning, and there will be helpful suggestions for SMEs on how to make the most of these developments. In order to achieve long-term success and a leg up in the digital economy, the conclusion stresses the need of using machine learning.

For the Chinese market, Liu et al. [18] constructed 34 stock price determinants and then used Bayesian optimization to train four models: RF, DNN, GBDT, besides Adaboost. These models are then used to predict the closing prices of innovative SMEs that too relisted the following day. This study covers the period from July 22, 2019, to September 10, 2021 and uses 78,708 samples from 337 SMEs listed on the STAR market. Based on the experimental results, the Random Forest (RF) and Deep Neural Network (DNN) models [16] outperformed the Gradient Boosting Decision Tree (GBDT) and Adaptive Boosting (AdaBoost) models in terms of the evaluation metrics: Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA), thereby demonstrating superior prediction performance.

In order to enhance manufacturing processes, particularly for SMEs, Cruz et al. [19] propose a methodology for incorporating a completely automated procedure that uses automated machine learning algorithm. The approach is based on using the created models as objective functions of a non-dominated sorting genetic procedure that uses reference points. This sorting algorithm then produces production processes that are pareto-optimal based on preferences. A small manufacturing enterprise's production process data was used to execute and evaluate the technique, which resulted in very accurate models for the indicators that to be analyzed. In comparison to the results achieved using the conventional trial-and-error approach that focused solely on productivity, step of the suggested methodology was able to raise manufacturing process productivity by 3.19% and decrease defect rate by 2.15%.

In order to boost teamwork among SMEs promote innovation, and drive economic development, Wang, & Zhang [20] suggested using the XGBoost procedure in conjunction with IoT data. Internet of Things (IoT) and machine learning's part in fostering long-term economic growth in specific areas. In today's cutthroat business environment, staying ahead of the curve requires constant technological innovation. This article takes a look at how geography and environmental factors have affected economic development in different parts of China. Through performance evaluation, it contributes to regional economic success by focusing on SME coupling and coordination. Integrating IoT devices gives SMEs access the real-time data, which allows them to get profound insights into production, supply networks, and consumer behavior. At the same time, the XGBoost algorithm evaluates the data effectively and finds useful insights. The data from 11 provinces along the Yangtze River economic belt shows that between 2015 and 2020, Jiangsu Province will have the best regional innovation performance. The practical outcomes, supported by datasets that combine data from these provinces, demonstrate the promise of this strategy driven by the Internet of Things and XGBoost. With an astounding accuracy rate of 91.7%, this research highlights how effective this integrated strategy is in optimizing SME processes, outperforming rival machine learning techniques RF, and LR. It also calculates the ranking of the innovation environment, the mean value. Across 30 provinces in China, the average innovation degree was 0.1624.

SMEs are an important part of most economies' job markets, and Litvinenco has [21] focused on assessing their credit risk. The regulator claims that there is a lack of practical application of ML approaches, even though these methods can improve capital requirements assessments and open up financial services to this segment. One possible explanation is that financial firms are compelled to utilize simpler models due to the total complexity of explainability and interpretability. The benefits of these techniques are not always obvious, which is another factor. This research suggests a decision tree/logistic regression hybrid model to solve the complexity issue. With interpretability complexity on par with logistic regression, this model outperforms Random Forest and XGBoost. Their purpose is to differentiate a model's misclassifications based on their capital significance and to give an idea of the total capital supplies that a model is capable of producing. By comparing the models using these and other generally used measures, the financial institutions are able to make a better-informed judgment on which model would best satisfy their objectives?

Using authorized invoice data from 425 SMEs in Chongqing, Huang et al., [22] has concentrated on company performance statistics. In order to understand the feature contribution of a particular output, a prediction classifier was built using logistic regression, random forest, support vector machine, and soft voting ensemble learning methods. This classifier was then merged with the SHAP value. Consequently, our study demonstrated a robust association between the extracted characteristics and future defaults, paving the way for the prediction of companies' financial success.

To address the issue of SMEs' unbalanced in SCF using deep learning (DRL), Zhang et al., [23] proposed a new method they term DRL-Risk. To propose an instance-based account, taking into account the actual damage caused SMEs, and formulates the ICRP process. To then suggest a decision-policy deep duelling neural network for predicting SMEs' credit risk. The DRL-Risk method can use deep reinforcement learning to focus on SMEs that are most likely to incur large losses financially. The experimental results show that when compared to the baseline approaches in recall, G-mean, and financial loss, the DRL-Risk methodology may greatly improve the performance of predicting the credit risk of SMEs in SCF.

III. Proposed Methodology

A. Data Collection

Although the organization has a production management information system, it does not have much of a presence on the Internet. In the absence of a comprehensive digital strategy, the company is contemplating the implementation of autonomous production processes, sensor networks for the Internet of Things, and predictive maintenance systems. It can take part in the flow of information between suppliers and customers to some extent.

The use of straightforward economic software facilitates interaction with other branches of governmental administration. Data becomes more important to a software-controlled, dynamic Internet presence. Supply besides demand chain info flows, such as collaborative virtual archives, real-time big data, are being considered as part of an overall digital strategy.

To fully understand how SMEs engage with cyber-physical smart factories, cognitive automation, and Industry 4.0 wireless networks, it is necessary to first address SMEs after a quick overview of the concept. According to the European Commission, the number of employees and revenue are the main requirements for qualifying SMEs.

These requirements are provided in Table I. Certain businesses are the only ones that must meet these standards [24]. Companies are considered small if they have less than 50 workers and yearly sales of up to €10 million, and medium-sized if they have less than 250 employees and yearly to €50m million, meaning they have a balance sheet of up to €43 million.

Table I shows that there are several ways in which businesses can be assessed for their preparedness for this undertaking. These range from strategy and organization to smart factories, manufactured commodities, decision-making processes driven by big data, and human resources [25]. In the methodical approach of secondary analysis, the research questions are formed initially, and then the dataset is located and evaluated in great detail. Consequently, the primary objective of determine which obstacles hinder European SMEs the most when it comes to implementing Industry 4.0. Researchers drew on a variety of secondary data sources—including peer-review the academic articles, books, government records, and company annual reports—to compile the information needed to complete the study.

TABLE I CATEGORIZATION OF SMES

Company Category	Turnover	Staff Headcount	Balance Sheet Total
Medium-sized	≤€50 m	<250	≤€43 m
Small	≤€10 m	<50	≤€10 m
Micro	≤€2 m	<10	≤€2 m

A variety of screening and quality evaluation methods were used in the analysis, including data from the European Commission, the Organisation for Economic Co-operation and Development (OECD), and tools such as Distiller Systematic Review (DistillerSR), Mixed Methods Appraisal Tool (MMAT), Risk of Bias in Systematic Reviews (ROBIS), and the Systematic Review Data Repository (SRDR).The SME Alliance's secondary data analysis was also used to perform the research. The following scientific procedures to be employed to data: i) the analytical technique that breaks down a large research problem into smaller ones in order to better understand it. In this study, the used: (i) analysis, which involved searching domestic and foreign literature in the designated research area for relevant information; (ii) synthesis, which involved processing and combining previously acquired knowledge; and (iii) comparison, which involved finding a knowledge, phenomena, or objects in order to learn more about the studied issue. (iv) the investigating strategy that was employed to discover more about the current issue. This method was utilized in this study to interpret the results of the analyses. Its purpose is to draw theoretical conclusions about the research problem based on the examined knowledge, which is prearranged dependencies. Comparative analysis was also a part of the investigation. Of the 268 companies surveyed in Germany, 56.5% did not fully comply with the requirements for implementing Industry 4.0 [26]. For the novice level 1 implementation approach, 20% of respondents are just somewhat prepared. Table II shows that just 0.3% met all five requirements at the exceptional level of execution.

To find out how ready companies are for Industry 4.0, a poll was run. Fifteen hundred chief executive officers (CXOs) from nineteen different nations took part. While 20% of chief executive officers said their companies are ready for a new business model, only 14% said to "extremely confident" in their ability to answer the problems of Industry 4.00. Despite the need for significant changes, 84% of educate their personnel and only 25% thought their employees to completely incorporate Industry 4.0. Less than one-fifth of people who took the survey felt adequately ready for intelligent and autonomous technologies. On a 15-year time frame, Fig. 1 shows the amount of SMEs in the EU [27]. The proliferation of these firms is plain to see.

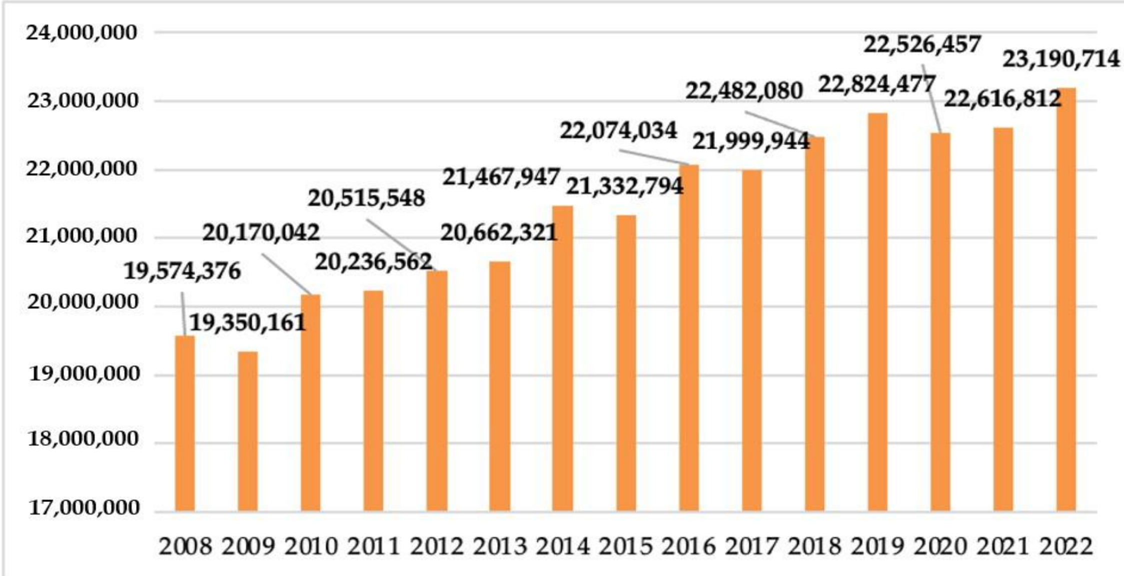

Fig. 1. Sum of SMEs in the European Union (EU27) from 2008 to 2022. Basis: Authors' gathering [27].

Nearly 23 million people called them home in 2022. The first step for SMEs is to automate their administrative and marketing processes. The hardest part of starting a business is often the first step. Strong technological complementarities might encourage future adoption after an initial shift to digital know-how. Many small and medium-sized enterprises (SMEs) depend on external systems, assistance, and guidance to accomplish these and other digital technology goals. There are financial considerations as they need to make up for a lack of internal capacity, thus this is done. Take digital platforms like e-commerce marketplaces and social networks as an example. They provide a great chance to improve some activities while keeping costs down, including data analytics and business intelligence services. To a similar extent, SMEs manage digital security risks by using external consultants or incorporating security-by-design into their digital services. Knowledge marketplaces provide AI solutions, and cloud-based software as a service allows them to skip the introduction of new AI systems. Autonomous mobile robots use cloud computing, image recognition, smart manufacturing, and real-time monitoring. The use of data analytics, imaging and sensing tools, and virtual reality simulations are all components of digital twin-driven smart manufacturing. In smart industrial settings, collaborative autonomous systems use cloud computing analytics, mobile robotic equipment, and tools for acquiring and analyzing images.

When it comes to digital disparities, technical complementarities might make things worse as bigger and better-informed companies can afford to use more sophisticated digital strategies. Enterprise CRM production process integration, and data analytics are all examples of more advanced technologies that highlight the gap between SMEs and larger companies.

It is necessary to high the benefits and drawbacks of Industry 4.0 technologies before assessing implementation hurdles. The irregularities in the deployment of Industry 4.0 must be described and characterized correctly. While there are certainly obstacles to overcome before big data-driven technologies can be completely utilized, industrial artificial intelligence can enhance production capabilities and productivity, leading to higher profitability. Rapid and configurable operations, including storage cost savings, allow for 10-30% cheaper costs in mass manufacturing, which is the greatest advantage of implementing Industry 4.0. Another perk is the possibility of a ten to thirty percent drop in logistics and quality control costs.

Worker output, environmental impact, and overall efficiency can all benefit from more effective use of energy and natural resources, which can boost productivity by 15–20%. Consequently, the manufactured goods may be made and delivered to clients faster. Industry 4.0 encourages steady economic expansion by highlighting state-of-the-art industrial manufacturing methods. There are ever-changing tests that SMEs face while trying to embrace Industry 4.0. Given the interconnected nature of the factors that slow down or speed up the adoption of new technology, this study will also evaluate the potential benefits of using the suggested deep learning model to help SMEs overcome implementation hurdles.

TABLE II STAGES OF IMPLEMENTATION

Level	Designation
0	Expert
1	Top Performer
2	Intermediate
3	Experienced
4	Top Performer
5	Intermediate

B. Contrastive Learning of Visual Representations

In order to forecast the output of data, the study makes use of deep learning. $E(\bullet)$ is the symbol for the encoder, which is able to transform the data into two representations, r' and r'', by removing any semantic information. The Vision Transformer

(ViT) [28] is a source of inspiration for our light encoder construction LTrans in our framework. It gets pictures r′ and r″ as Eq. (1) shows, where the yield $r' \in R^d$ is created layer.

$$r' = e(i') \tag{1}$$

To change the input of the standard Transformer—a 1D embeddings—into a series of 2D flattened patches with dimensions N × P2 • C, instead of the data being reshaped from H × W × C. The original data's height and width are indicated by the H and W in this case. The size of the C stands for the number of channels. Each data patch's resolution, denoted as P2, and the total number of patches are determined by Eq. (2).

$$N_{patch} = (HW \vee P)^2 \tag{2}$$

To first flatten the patches using the original data shaper, then project them into D dimensions using a linear projection with trainable parameters. In Eq. (3), we can see the linear projection, with ip standing for the 2D patches that are flattened from the initial data set i. An i_class is a unique token for a categorization. This is very much like the BERT [CLS] token [29]. Patch embeddings are the results of this projection. The position embeddings are put to use, $e_{position}$ to maintain the data regarding the positions. To generate position embeddings using typical learnable 1D methods, then combine them embeddings to form the final embedded patches E_0. Afterwards, the LTrans is fed embedded patch data.

$$E_0 = e_{position} + \left[i_{class}; i_p^1 e; i_p^2 e; \ldots; i_p^N e\right], e \in R^{(P^2.C)\times D}, e_{position} \in R^{(N+1)\times D} \tag{3}$$

To add a normalization every component and a residual both component to LTrans, which comprises of MLP blocks. A large number of academics are interested in incorporating multi-head attention into their models. To be more specific, let's pretend to have an input sequence$x \in R^{N\times D}$. To calculate sum over each charge V in the input arrangement x, as Eq. (4) shows. The sights of attention $Attention_{mn}$ are found by comparing the query representations of two elements in the arrangement and their pairwise similarity. Q^m and key K^n, as Eq. (5) shows. Lastly, Sa is calculated by the Eq. (6).

$$[Q, K, V] = xU_{QKV}, U_{QKV} \in R^{D\times 3D_h} \tag{4}$$

$$Attention = softmax\frac{QK^T}{\sqrt{D_h}}, Attention \in R^{N\times N} \tag{5}$$

$$Sa(x) = AttentionV \tag{6}$$

The outputs of k self-attention procedures are projected together by multi-head self-attention (MSA), as demonstrated in Eq. (7).

$$MSA(x) = [Sa_1(x); Sa_2(x);, \ldots Sa_k(x)]U_{QKV}, U_{QKV} \in R^{k.D_h\times D} \tag{7}$$

Two completely linked layers with GELU non-linearity make up the MLP chunks in the LTrans. In Eq. (8) and Eq. (9), the full Ltrans procedure is detailed.

$$x_l' = MSA\big(Norm(x_{l-1})\big) + x_{l-1}, l = 1 \ldots L \tag{8}$$

$$x_l = MLP\big(Norm(x_l')\big) + x_l', l = 1, \ldots, L \tag{9}$$

Projection head $p(\cdot)$may transpose the illustration r to a different feature interplanetary z using a tiny non-linear multi-layer perceptron neural network. The F is a non-linear ReLU function, as seen in Eq. (10). The $W^{(1)}$ is encoder $e(\cdot)$, and the $W^{(2)}$ is weight projection head $p(\cdot)$.

$$z = p(r) = W^{(2)}\sigma\big(W^{(1)}r\big) \tag{10}$$

Our final model is the result of combining the four parts listed above. This algorithm determines to have size N, constant τ, encoder e, projection head p, and data expansion module A. pass the data into the encoder $e(\cdot)$ and projection head $p(\cdot)$. After that, to do the pairwise similarity and calculate the encoder $e(\cdot)$ besides forecast head $p(\cdot)$. Finally, to produce a network$e(\cdot)$, then head. To will use this encoder $e(\cdot)$in order to create the unlabeled dataset's foundational data representations, and then feed that knowledge into our model so it can perform the classification task.

- Underlying Knowledge Based Multi-Layer Perceptron Classifier (UKMLP)

With the help of the restricted labelled data, the UKMLP attempts to refine the feature representation learnt by the aforementioned model. Here, to take a page out of transfer learning's playbook by enhancing the traditional classifier's architecture. Specifically, to add 12 hidden layers, with the following configuration: three layers of 256 layers of 512 neurons connected, two layers of 1024 connected, and three layers of 256 neurons connected. The three components of the design are the input layer, two hidden layers, and the output layer. After receiving input from model up top, the underlying knowledge is passed on to the buried layers. The output layer's neuron counts changes depending on the dataset's classes. As shown in Eq. (11) it adheres to a rectified linear activation for every hidden layer. If x is less than zero, the ReLU function returns zero as an output; otherwise, it returns the input value.

$$f(x) = max(0, x) \tag{11}$$

The UKMLP loss function, multi-class entropy, is illustrated in equation (12). Here, yˆ vector y containing the actual class label, is a one-hot representing the predicted class probabilities for all C classes, and the natural logarithm is represented by the log.

$$L(y^\wedge, y) = -\sum_{i=1}^{C} \quad y_i log(y^\wedge{}_i) \tag{12}$$

- Fine-tuning using Artificial protozoa optimizer

Here to present the APO algorithm, which is used to fine-tune the UKMLP model's parameters using its mathematical models that mimic protozoa.

1) Mathematical models: This section presents the algorithm that can be used to solve the minimization problem. For metaheuristic algorithms, the solution set representation is crucial. Each protozoan in our suggested method occupies a certain location inside the solution set, which is represented by dim variables.

2) Foraging: When studying protozoa foraging behavior, to took both internal and extrinsic influences into account. The protozoa's feeding habits are an example of an internal factor, whereas species collisions and competing behaviors are examples of external variables.

3) Autotrophic mode: In order to sustain themselves, protozoans can use chloroplasts to make carbs. The protozoan will relocate to a spot with lo To r light intensity if it is exposed to very bright light. When it's in a dimly lit area, the inverse is true. Taking into consideration the light levels surrounding the jth protozoan is suitable will move to the site of the jth protozoan. Our mathematical model for mode is as follows:

$$X_i^{new} = X_i + f. \tag{13}$$

$$X_i = \left[x_i^1, x_i^2, \dots, x_i^{dim}\right] X_i = sort(X_i) \tag{14}$$

$$f = rand.\left(1 + cos\left(\frac{iter}{iter_{max}}.\pi\right)\right) \tag{15}$$

$$np_{max} = \left[\frac{ps-1}{2}\right] \tag{16}$$

$$w_a = e^{-} \tag{17}$$

$$M_f[d_i] = \{1, if\, d_i is \in randperm\left(dim, \left[dim.\frac{i}{ps}\right]\right)\ 0, otherwise \tag{18}$$

where X_i^{new} and X_i denote the efficient position, besides original site of the ith protozoan, respectively. X_j is the randomly designated jth protozoan. X_{k-} Represents a randomly selected protozoan in the kth paired than i. Precisely, if X_i is X_1, X_{k-} is also set as X_1. X_{k+} denotes a haphazardly s kth paired neighbor, besides its rank directory is greater than i. Particularly, if X_i is X_{ps}, X_{k+} is also set to X_{ps}, where ps is the population size. f represents a foraging factor and $rand$ denotes a random number in the distribution. $iter$ besides $iter_{max}$respectively. np indicates the number of neighbor pairs among the external factors and $npmax$ is the maximum charge of np. w_a is mode and $eps(2.2204e - 16)$ is a significantly small sum. $\odot$ denotes the Hadamard product. M_f is a size of $(1 \times dim)$, where every element is 0 or 1. d_i index $d_i \in \{1,2, \dots, dim\}$.

- Heterotrophic style

A protozoan can get its nourishment by soaking up organic stuff when it's dark. With the expectation that X_{near} is close by and has plenty of food, the protozoan will go there. This mathematical model is proposed for the heterotrophic mode.

$$X_i^{new} = X_i + f\left(X_{near} - X_i + \frac{1}{np}.\sum_{k=1}^{np} w_h.(X_{i-k} - X_{i+k})\right) \odot M_f \tag{19}$$

$$X_{near} = \left(1 \pm Rand.\left(1 - \frac{iter}{iter_{max}}\right)\right) \odot X_i \tag{20}$$

$$w_h = e^{-\left|\frac{f(X_{i-k})}{f(X_{i+k})+eps}\right|} \tag{21}$$

In order to sustain themselves, protozoans can use chloroplasts to make carbs. The protozoan will relocate to a spot with light intensity if it is exposed to very bright light. When it's in a dimly lit area, the inverse is true. Taking into consideration the light levels surrounding the jth protozoan is suitable will move to the site of the jth protozoan. Our mathematical model for mode is as follows:

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$$w_h = e^{-\left|\frac{f(X_{i-k})}{f(X_{i+k})+eps}\right|} \tag{21}$$

$$Rand = [rand_1, rand_2, \dots, rand_{dim}] \tag{22}$$

where X_{near} is a nearby site, and ‘‘±’’ implies that $Xnear$ can be in dissimilar instructions from the ith protozoan. X_{i-k} denotes the $(i-k)$th protozoan the kth paired index is $i-k$. Specifically, if X_i is X_1, X_{i-k} is also set to X_1. X_{i+k} represents the $(i+k)$th protozoan designated from the kth paired index is $i+k$. Particularly, if X_i is X_{ps}, X_{i+k} is also set to X_{ps}. w_h is factor in the heterotrophic mode. $Rand$ is elements in the [0,1] intermission as given in Eq. (22).

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4) Dormancy: As a defense mechanism against harsh environments, protozoans can go into a dormant state when threatened. In order to keep the number of protozoa constant, they replace dormant protozoans with newly created ones. The following is the mathematical model of dormancy:

$$X_i^{new} = X_{min} + Rand \odot (X_{max} - X_{min}) \quad (23)$$

$$X_{min} = [lb_1, lb_2, \dots, lb_{dim}]\ X_{max} = [ub_1, ub_2, \dots, ub_{dim}] \quad (24)$$

where X_{min} and X_{max} represent the vectors, respectively. lb_{di} and ub_{di} indicate the of the dith variable, correspondingly.

5) Reproduction: When protozoa are mature and in good health, they reproduce asexually by a process called binary fission. This kind of reproduction should theoretically result in the protozoan dividing into two females that are genetically identical. To able this behavior by creating an identical protozoan and then taking perturbation into account. How about this for a mathematical model of reproduction:

$$X_i^{new} = X_i \pm rand.\left(X_{min} + Rand \odot (X_{max} - X_{min})\right) \odot M_r \quad (25)$$

$$M_r[d_i] = \{1, if\, d_i is \in randperm(dim, [dim.rand])\ 0, otherwise \quad (26)$$

where ‘‘±’’ implies alarm forward besides reverse. Mr is vector in replica procedure, whose size is $(1 \times dim)$, besides each element is 0 or 1.

6) Algorithm: Here are the specifics of the APO. Here are the parameters that are involved in integrating all the mathematical models:

$$pf = pf_{max}.rand \quad (27)$$

$$p_{ah} = \frac{1}{2}.\left(1 + cos\left(\frac{iter}{iter_{max}}.\pi\right)\right) \quad (28)$$

$$p_{ar} = \frac{1}{2}.\left(1 + cos\left(1 - \frac{i}{ps}.\pi\right)\right) \quad (29)$$

where pf is a quantity fraction of latency besides reproduction in protozoa populace and pf_{max} is the maximum charge of pf. p_{ah} designates the likelihoods of heterotrophic behaviors, and p_{dr} designates the likelihoods of dormancy besides imitation.

Note that the projected APO has limits: np (sum of neighbor pairs) and pf_{max} (maximum proportion fraction).

IV. Results and Discussion

An NVIDIA TESLA P100 GPU with 16 GB of RAM and a XEON CPU of 13 GB RAM are used to execute the experiments in the study. The model's hyper-parameters are defined as follows: epochs=200, batch size=500, learning rate=0.01, projection dimension=64. Keras is used to implement the code with scikit-learn. Compare the proposed model to current methods using a variety of metrics in Table III, which displays the results of the validation analysis.

TABLE III COMPARATIVE ANALYSIS OF PROPOSED MODEL WITH EXISTING MODELS

Model	MAPE	MSE	RMSE	R2
DBN	41.6	0.021	0.144	0.776
CNN	39.29	0.020	0.132	0.805
LSTM	52.99	0.019	0.245	0.735
Proposed model	29.95	0.013	0.116	0.905

Table III and Fig. 2 presents a comparative investigation of the planned model against existing models (DBN, CNN, and LSTM) using presentation metrics such as MAPE, MSE, RMSE, besides R^2. The proposed model shows the best performance with the lowest MAPE of 29.95, significantly outperforming DBN (41.6), CNN (39.29), and LSTM (52.99). For MSE, the proposed model also achieves the lowest value at 0.013, compared to DBN (0.021), CNN (0.020), and LSTM (0.019). In terms of RMSE, the projected model exhibits the smallest error at 0.116, while DBN, CNN, and LSTM have values of 0.144, 0.132, besides 0.245, correspondingly. Finally, the R^2 charge of the projected model is the uppermost at 0.905, indicating superior predictive accuracy compared to DBN (0.776), CNN (0.805), and LSTM (0.735). Overall, the proposed model significantly outperforms existing models across all metrics.

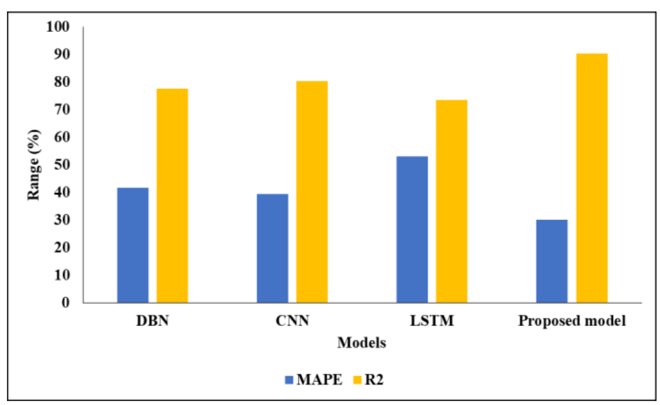

Fig. 2. Visual representation of proposed model.

TABLE IV ERROR ANALYSIS OF DIFFERENT MODELS

Metric	Algorithm				
	Proposed	LSTM	RNN	CNN	DBN
R2	0.98	0.96	0.956	0.94	0.93
Mean Squared Error (MSE)	0.0065	0.042	0.037	0.036	0.0325
Root Mean Squared Error (RMSE)	0.0803	0.095	0.091	0.099	0.108
Mean Absolute Percentage Error (MAPE)	0.0702	0.0966	0.086	0.089	0.0938
Mean Absolute Error (MAE)	0.0567	0.0634	0.0648	0.0743	0.1305

1) Comparative Analysis of Proposed model on error analysis

The error analysis of various algorithms is tested and results are averaged in Table IV.

In the analysis of R2, the existing ML and DL models are tested and achieved nearly 93% to 95%, where LSTM achieved 96% and proposed model achieved 98%. This is because the research work uses the optimizer for fine-tuning the parameters of the proposed model and existing models uses the manual learning rate and leads to high computational complexity. The existing DBN achieved 0.03 of MSE and 0.108 of RMSE, where RNN achieved 0.037 of MSE and 0.091 of RMSE and leads to high computational complexity issues than proposed model. The MAE of proposed model has only 0.0567 and the existing ML and DL achieved nearly 0.064 to 0.074 of MAE leads to increase the chance of error rate in detecting process. From the analysis, it is clearly shown that the proposed model achieved better performance than existing models such as DBN, CNN, RNN and LSTM models.

2) Experimental analysis of the proposed model on different iterations

Table V and VI presents the experimental analysis of proposed model on different iterations by considering with and without APO optimizer.

The performance of the proposed model was evaluated in terms of error metrics, including R-squared (R2), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE), across multiple iterations. The results were analyzed both without optimization and with the APO optimizer. Table V presents the error analysis of the proposed model across 10 iterations without optimization. The average R2 value achieved is 0.9950, indicating strong predictive performance. However, the other error metrics show fluctuations across different iterations. Notably, iteration 2 exhibits a lower R2 value (0.9893) and higher error values (MSE = 0.0312, RMSE = 0.1766, MAPE = 0.0255, and MAE = 0.1263), suggesting reduced accuracy in that particular run. Conversely, iteration 10 records a higher R2 value (0.9979) and lower MSE (0.0056), RMSE (0.0748), MAPE (0.0097), and MAE (0.0559), indicating more stable performance. The inconsistency in error values suggests that without optimization, the model exhibits variability in prediction accuracy across iterations.

TABLE V ERROR ANALYSIS OF PROPOSED MODEL ON DIFFERENT ITERATIONS

Number of iterations	Proposed with various iteration without optimization				
	R2	**MSE**	**RMSE**	**MAPE**	**MAE**
1	0.9981	0.0052	0.0721	0.0099	0.0529
2	0.9893	0.0312	0.1766	0.0255	0.1263
3	0.9975	0.0066	0.0815	0.0095	0.0501
4	0.9927	0.0212	0.1456	0.0216	0.1101
5	0.9928	0.0211	0.1454	0.0210	0.1090
6	0.9977	0.0060	0.0777	0.0100	0.0560
7	0.9934	0.0194	0.1391	0.0207	0.1055
8	0.9978	0.0060	0.0772	0.0096	0.0529
9	0.9926	0.0216	0.1471	0.0219	0.1110
10	0.9979	0.0056	0.0748	0.0097	0.0559
Average	0.9950	0.0144	0.1137	0.0159	0.0830

TABLE VI ANALYSIS OF PROPOSED MODEL IN TERMS OF ERROR RATE WITH APO OPTIMIZER

Number of iterations	various iteration with optimization				
	R2	**MSE**	**RMSE**	**MAPE**	**MAE**
1	0.9981	0.0048	0.0690	0.0078	0.0460
2	0.9970	0.0054	0.0738	0.0097	0.0608
3	0.9973	0.0072	0.0849	0.0115	0.0616
4	0.9986	0.0032	0.0567	0.0100	0.0517
5	0.9975	0.0069	0.0828	0.0135	0.0697
6	0.9992	0.0029	0.0541	0.0088	0.0510
7	0.9992	0.0016	0.0399	0.0053	0.0338
8	0.9975	0.0071	0.0843	0.0133	0.0689
9	0.9983	0.0041	0.0638	0.0123	0.0596
10	0.9960	0.0114	0.1069	0.0164	0.0858
Average	0.9978	0.0055	0.0716	0.0109	0.0589

Table VI presents the performance of the model when optimized using the APO optimizer. The results indicate a notable improvement in performance. The average R2 value increases to 0.9978, demonstrating enhanced model reliability. Additionally, the error values significantly decrease, with MSE dropping to 0.0055, RMSE to 0.0716, MAPE to 0.0109, and MAE to 0.0589. The lowest MSE value (0.0016) and RMSE value (0.0399) occur in iteration 7, corresponding to an exceptionally high R2 value of 0.9992, signifying excellent model accuracy. The highest error values are observed in iteration 10 (MSE = 0.0114, RMSE = 0.1069, MAPE = 0.0164, MAE = 0.0858), yet these values remain significantly lower compared to the non-optimized model.

A comparison between the two approaches clearly demonstrates the advantage of using the APO optimizer. The reduction in error values across all metrics indicates that the optimization process successfully enhances model accuracy and stability. Notably, APO optimization effectively minimizes variations in model performance, ensuring consistency across iterations. The improvement in R2 values confirms that the optimized model maintains a stronger correlation between predictions and actual values, leading to more reliable outcomes.

V. CONCLUSION

This study identified lack of capital and skilled workforce as the primary barriers preventing European SMEs from adopting Industry 4.0 technologies. Successful implementation depends not only on financial resources but also on strong leadership, strategic planning, and continuous skill development. The proposed model can guide SMEs in prioritizing digitalization steps and securing support through training and funding schemes. Importantly, Industry 4.0 is not exclusive to large firms—SMEs, with proper planning and resources, can also participate effectively. Future work will focus on developing cost-efficient AI-based training platforms to upskill SME workforces in Industry 4.0 technologies. Integration of real-time data from SME pilot implementations can further validate the UKSSL framework. Research can also explore decentralized financing models to ease capital constraints. Additionally, collaborative innovation hubs may support knowledge sharing and reduce adoption barriers.

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