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Enhancing supply chain efficiency in textiles: a deep learning approach to Industry 4.0 implementation

Younes Jamouli
Higher School of Textile and Clothing Industries, Km. 8, BP 7731, Q. Laymoune - Oulfa 20200 Casablanca, Morocco, jamouli@esith.ac.ma (corresponding author)
Mouhsene Fri
Euromed University of Fes, UEMF, BP 51, Fès, Morocco, m.fri@ueuromed.org
Aziz Soulhi
National Higher School of Mines, Avenue Hadj Ahmed Cherkaoui - BP 753, Agdal, Rabat, Morocco, soulhi@enim.ac.ma
Fayçal Fedouaki
National Higher School of Arts and Professions, Hassan II University, 150 Avenue Nil, Casablanca, Grand Casablanca 20670, Morocco, fedouaki.fayçal@gmail.com

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Abstract: Moroccan textile SMEs face increasing pressure to adopt Industry 4.0 (I4.0) technologies to enhance their competitiveness and improve their supply chains. However, a lack of clear implementation strategies, particularly regarding action prioritization, hinders their progress. This research addresses this challenge by developing an intelligent framework, grounded in Deep Learning, to guide I4.0 implementation for these SMEs. The framework leverages two key inputs: the Smart Industry Readiness Index (SIRI) dimensions, providing a structured assessment of the enterprises' current maturity across Process, Technology, and Organization, and Critical Success Factors (CSFs), identified through the DEMATEL method, capturing expert knowledge on the drivers of successful I4.0 adoption. The core of the framework is a set of specialized neural network architectures, trained to forecast the appropriate priority domain for I4.0 deployment. These specialized models, including the RNN with Attention (for Organization Priority) and the CNN-LSTM with Attention (for Technology and Process Priority), enable a nuanced and context-aware prioritization of actions. Key performance indicators show high accuracy in determining the appropriate focus area for Industry 4.0 deployment: the RNN with Attention architecture achieves 84.3% accuracy for Organization Priority, the CNN-LSTM with Attention achieves 93.3% for Technology Priority, and 83.3% for Process Priority. This data-driven and expert-informed prioritization approach offers a practical and actionable roadmap for Moroccan textile SMEs to optimize their limited resources and maximize the impact of their digital transformation efforts, ultimately contributing to a more competitive and sustainable sector.

1 Introduction

Moroccan textile SMEs face challenges in adopting Industry 4.0 (I4.0), a global initiative driving production transformation through digital technologies [1]. Technologies of Industry 4.0 are crucial in the supply chain and logistics as they enable smart automation, real-time visibility, and process optimization, thereby transforming operational efficiency and responsiveness to market demands. The lack of a clear roadmap impedes this adoption. This article proposes a Deep Learning-based intelligent framework to prioritize I4.0 actions, integrating SIRI dimensions [2] and critical success factors (CSFs) [3-7].

The Moroccan textile sector, a key economic pillar, needs enhanced competitiveness amid global pressures. I4.0 offers unique potential but demands a holistic and SME-adapted approach, aligning with Digital Morocco 2030's aims to accelerate digital transformation [8].

This research advances I4.0 in Moroccan textiles by developing an action prioritization framework that is:

- Adapted to Moroccan textile SMEs.
- Based on empirical data and rigorous analysis.
- Actionable and easy to implement.
- Dynamic and scalable.

Empowered by SIRI and CSFs, the Deep Learning models (RNN, CNN, CNN-LSTM with self-attention) identify critical action domains (process, technology, organization) for each company, considering their specific context. Using a test dataset and hyperparameter tuning, the proposed model can determine the appropriate priority for I4.0 deployment. The application of the trained neural network was discussed to ensure the success of this digital transformation project. The primary goal of this study is to obtain the necessary data and connect them (Figure1).

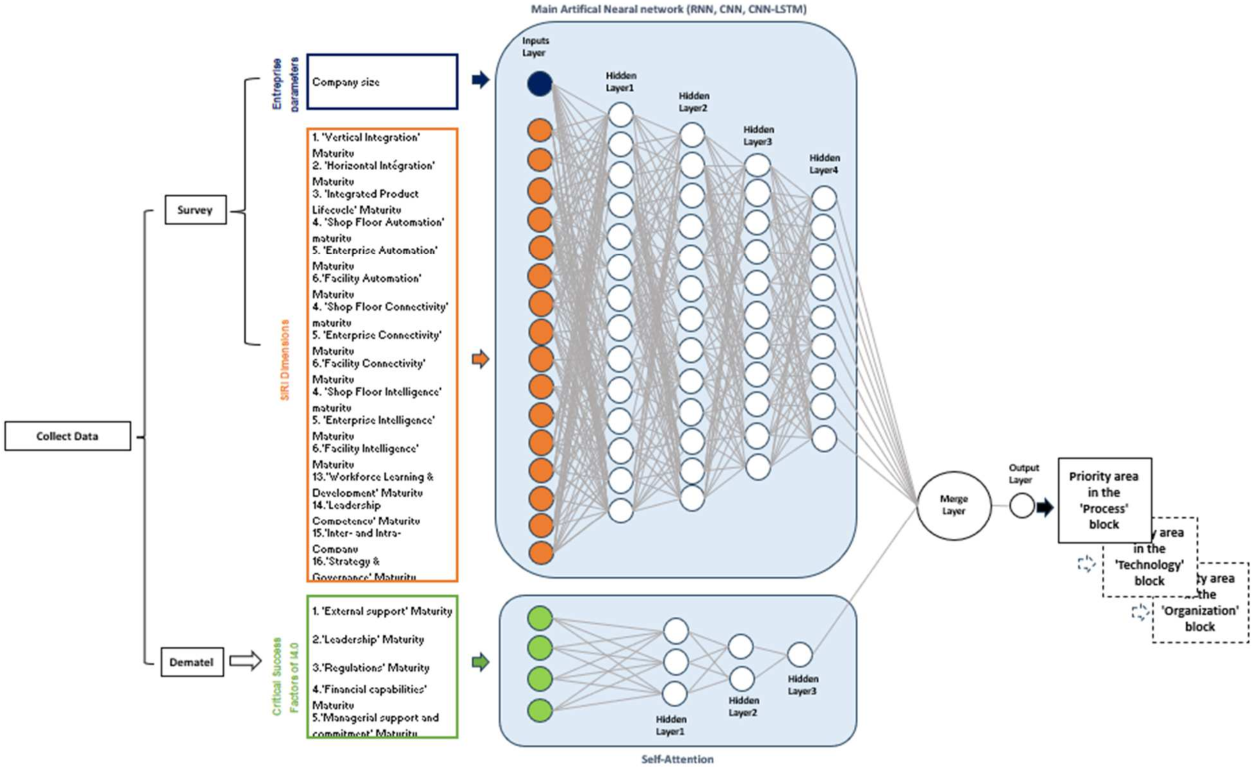


Figure 1 Neural network model input and output

Data for this research, collected from multiple sources, includes: (1) the maturity of critical success factors (CSFs) relevant to Industry 4.0, assessed separately using a Likert scale, reflecting the effort required to achieve each CSF and the extent to which it is integrated into the business [9]; (2) implementation priorities selected by the participating companies themselves; and (3) company size. The study aims to prioritize one focus area (Process, Technology, Organization) per SIRI framework building block. Due to the problem's inherent complexity and the large number of variables involved, a trained neural network model is employed to provide a data-driven solution (Figure 1). The selection of the apparel and textile industry is justified by its reliance on price competitiveness and intolerance for waste in the Moroccan context.

The manuscript's structure is as follows: Session 2 details the SIRI Framework and presents common Industry 4.0 CSFs derived from the literature. Session 3 outlines the three-step methodology: expert verification of CSFs, recording CSF and SIRI dimension maturity using a Likert scale, and utilizing a neural network to forecast the appropriate priority. In the second stage, the trained neural network uses the reliable database of CSF and dimension maturity as inputs (Figure 1) to determine priority across different company sizes. The graphical and numerical results are illustrated in Session 4, while Session 5 concludes the paper with a suggested expansion of the model to prepare for the Industry 4.0 implementation stage in a clothes company.

2 Industry 4.0 Critical Success Factors (CSFs) and SIRI framework

2.1 *Industry 4.0 Critical Success Factors*

Recognizing the importance of Industry 4.0 for manufacturing SMEs, research has extensively investigated Critical Success Factors (CSFs) through literature reviews, Delphi studies, and case studies [3-6,10]. A synthesis of this research identifies 15 key CSFs for manufacturing SMEs [11]. Further analysis using DEMATEL reveals a hierarchical structure, identifying 5 influencing CSFs that drive the remaining 10: External Support, Leadership, Regulations, Financial Capacities, and Managerial Support & Commitment. Strategically prioritizing these 5 "cause" CSFs is crucial for accurately measuring firms' I4.0 readiness and ultimately enabling successful adoption. Specifically, effectively managing these CSFs in the pre-implementation phase requires preparing them for the subsequent implementation of I4.0 dimensions as a top priority. To ensure the appropriateness of all variables for the model, data was carefully prepared, as described in the following section.

2.2 *SIRI dimensions*

Our previous study aimed to assess the Industry 4.0 maturity level of Moroccan apparel manufacturing companies and to examine disparities in their strategies for I4.0 implementation. The Singapore Industry 4.0 Readiness Index (SIRI), known as "the Index," was selected as the primary evaluation tool due to its multifaceted nature (Figure 2) [12], providing insights into both current and future improvement plans. With government support, the Index is also tailored to SMEs and MNCs, emphasizing practical application. Focusing specifically on Moroccan companies, particularly in the apparel sector, the study assesses their maturity levels. Furthermore, to prioritize areas for improved digital maturity, an empirical study was conducted to understand their current I4.0 preparedness and to suggest a path for the textile and clothing industry to bridge the gap in I4.0 evaluation campaigns. However, the SIRI priority matrix insists on concurrently implementing the three Industry 4.0 building blocks, which raises the issue of appropriate and productive sequencing in the literature [12-14]. The core challenge lies in defining the most suitable priority of the 16 SIRI dimensions or defining a combination of three focus areas (one per building block) to improve digital maturity. Therefore, a successful deployment of Industry 4.0 depends on insightful implementation priority.

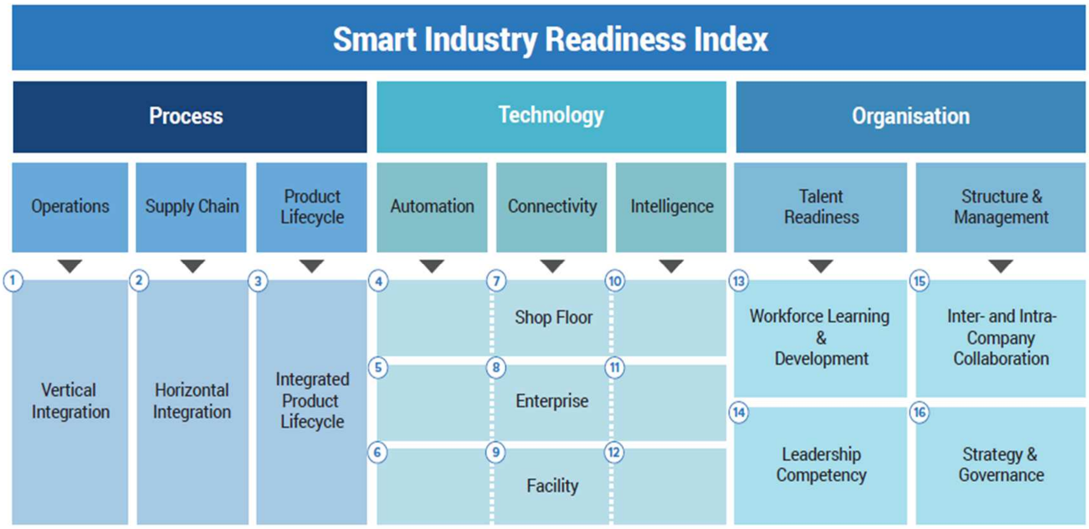


Figure 2. Singapore industry readiness index “SIRI”

3 Methods

Neural networks and deep learning algorithms offer excellent alternatives for addressing problems requiring training and data-driven insights [15]. Unlike many heuristic methods, deep learning operates without predefined calculation rules, instead learning robust relationships between focus area priorities (outputs) and various inputs: CSF maturity and SIRI dimensions maturity.

Aligned with the SIRI Framework, which structures Industry 4.0 around three building blocks – Processes, Technology, and Organization – this research aims to predict one area of intervention per building block. To achieve this, a predictive model based on three neural network models with self-attention was chosen. Self-attention empowers the model to weigh the significance of different elements in a sequence relative to each other, capturing long-range dependencies by computing attention scores based on relationships within the input sequence.

Specifically, self-attention is applied to the Critical Success Factors derived from our DEMATEL analysis. By adding Self-Attention mechanisms, these models can become even more powerful for tasks involving sequential or structured data, neural network models are popular architectures in the field of deep learning. A limitation, however, is the scarcity of extensive datasets representing real-world Industry 4.0 implementation scenarios. To address this, the results of our maturity assessment study within the Textile and Clothing sector in Morocco are used as a basis for training our model.

As depicted in Figure 1, the predictive model for the focus area priority dimensions of the three building blocks uses 22 input data and 1 output data. Among the input data, 1 relates to company size, 16 to the maturity of the SIRI dimensions, and 5 to the maturity of the Critical Success Factors. The output is linked to the focus area priority of the building block dimensions. Models are computed 3 times, each time with a different output: The priority dimensions of the Process building block, the priority dimensions of the Technology building block, and the priority dimensions of the Organization building block.

3.1 Data collection

This study measured the digital maturity of companies of varying sizes, linking their implementation strategies to different prioritized focus areas. Practitioners managing at least one Industry 4.0 project were required for participation. Data was gathered through an online survey, using the SIRI model [16] to assess digital maturity. Respondents rated the following dimensions on a scale of 0 to 5 (according to the SIRI index): Process (vertical integration, horizontal integration, integrated product lifecycle); Technology (shop floor automation, connectivity, and intelligence; company automation, connectivity, and intelligence; facility automation, connectivity, and intelligence); Organization (employee training & development, leadership skills, inter- and intra-company collaboration, strategy and governance). The average readiness index values for each dimension were gathered across the 252 participating businesses, providing an overview of I4.0 readiness for Moroccan textile and apparel manufacturers. These firms have an average readiness index of 0.95, compared to 1.04 for the average global textile company and 3.19 for global "best in class" companies [16]. Survey participants also measured the maturity of I4.0 critical success factors (CSFs) using a five-point Likert scale (1= not Mature to 5 = Totally Mature). All input variables were encoded as integers and converted to one-hot encoding format. Guided by the SIRI prioritization principle, successful Industrie 4.0 implementation requires the simultaneous development of the 3 building blocks.

3.2 Data Pré-processing

To ensure data integrity for subsequent analysis, all original data values were converted to a numeric format, and rows containing any missing values were removed. After removing irrelevant columns from the feature set, the 'Priority' column was designated as the target variable. The remaining columns were retained as primary characteristics, with a specific subset of feature columns (the CSFs maturity columns) isolated for use in the attention mechanism. The target variable was encoded into integers using Label Encoder and then transformed into a one-hot encoding format for compatibility with the classification model. To ensure a uniform scale across all features, the remaining features and attention columns were independently normalized using StandardScaler. Following normalization, Principal Component Analysis (PCA) was optionally applied to reduce dimensionality while preserving maximum information. To address class imbalance, the data was balanced using the RandomOverSampler oversampling technique. Finally, the data was partitioned into training and test sets using Train_test_split, with an 80/20 split. This rigorous pre-processing pipeline ensures clean, normalized, and correctly structured data, which is essential for enhancing the quality and performance of the trained neural network model's predictions.

3.3 Training of our three neural network-based models

Neural networks, composed of interconnected processing elements called "neurons," are powerful tools for establishing complex relationships between inputs and outputs [17]. Our neural network employs a three-layer hidden architecture, mapping *R* inputs (I) to *S* outputs (O). Each neuron sums its weighted inputs and adds a bias, feeding the result into an activation function to generate the output. The inherent complexity of neural network design stems from the numerous variables influencing training, such as the choice of learning algorithm, the number of neurons in the hidden layers, the connections between neurons and layers, the error function, and the activation function [18]. Consequently, hyperparameter tuning, a technique for selecting algorithm parameters to achieve an optimal solution dependent on these hyperparameters, is a critical step in enhancing neural network outcomes [19]. In this study, the Adam optimizer was utilized.

Table 1 Hyperparameters combinations

<table>
<tr><th>Model</th><th>Phase</th><th>Layer Type</th><th>parameters of layers</th></tr>
<tr><td rowspan="8">CNN with Attention</td><td rowspan="4">Phase 1</td><td>Conv1D</td><td>Filters: 64, Kernel size: 3, Activation: ReLU</td></tr>
<tr><td>BatchNormalization</td><td>Standard normalization</td></tr>
<tr><td>MaxPooling1D</td><td>Pool size: 2</td></tr>
<tr><td>Flatten</td><td>Flattens the input</td></tr>
<tr><td rowspan="3">Phase 2</td><td>Dense</td><td>Units: 128, Activation: ReLU</td></tr>
<tr><td>Attention (Self-Attention)</td><td>Applies self-attention to features</td></tr>
<tr><td>Flatten</td><td>Flattens the input</td></tr>
<tr><td>Merge</td><td>Dense</td><td>Units: Number of classes (softmax output)</td></tr>
<tr><td rowspan="5">RNN with Attention</td><td rowspan="2">Phase 1</td><td>SimpleRNN</td><td>Units: 64, Activation: ReLU, Return sequences: True</td></tr>
<tr><td>BatchNormalization</td><td>Standard normalization</td></tr>
<tr><td rowspan="2">Phase 2</td><td>Dense</td><td>Units: 128, Activation: ReLU</td></tr>
<tr><td>Attention (Self-Attention)</td><td>Applies self-attention to features</td></tr>
<tr><td>Merge</td><td>Dense</td><td>Units: Number of classes (softmax output)</td></tr>
<tr><td rowspan="8">CNN-LSTM with Attention</td><td rowspan="5">Phase 1</td><td>Conv1D</td><td>Filters: 64, Kernel size: 3, Activation: ReLU</td></tr>
<tr><td>BatchNormalization</td><td>Standard normalization</td></tr>
<tr><td>MaxPooling1D</td><td>Pool size: 2</td></tr>
<tr><td>LSTM</td><td>Units: 128, Return sequences: True</td></tr>
<tr><td>BatchNormalization</td><td>Standard normalization</td></tr>
<tr><td rowspan="2">Phase 2</td><td>Attention (Self-Attention)</td><td>Applies self-attention to LSTM output</td></tr>
<tr><td>Flaten</td><td>Flattens the input</td></tr>
<tr><td>Merge</td><td>Dense</td><td>Units: Number of classes (softmax output)</td></tr>
</table>

Table 1 details the specific hyperparameter combinations employed for our models' learning algorithm. Our setup involves setting three hyperparameters per network for the Main Network: Flattening Layers, Number of Dense Layers, Dropout, and Learning Rate (initially 0.001, dynamically reduced to 0.0005), and hyperparameters for the self-Attention Network: Number of Dense Layers, Internal Attention Layers, and Flattening Layers. Finally, a fusion layer parameter is also involved. Multiple alternatives were evaluated.

This study will employ a widely used hyperparameter optimization technique, chosen for its proven ability to deliver strong empirical results in tuning neural network performance.

4 Results and discussion

4.1 The proposed framework

✓ CNN with attention

The CNN with Attention model uses a Conv1D layer (64 filters, kernel size 3) followed by Batch Normalization and MaxPooling1D in its first phase to extract features from the SIRI dimensions. These features are flattened and combined with the attention-weighted DEMATEL factors. A Dense layer (128 units), and another Dense layer followed by a Softmax output layer predicts the priority domain.

✓ RNN with attention

The RNN with Attention model employs a Simple RNN layer (64 units, return sequences=True) followed by Batch Normalization in its first phase to process the SIRI dimension data sequentially. The resulting sequential features are then fed into a Dense Layer of 128 units, where they are integrated with the attention-weighted DEMATEL factors. A final Dense layer predicts the priority domain.

✓ CNN-LSTM with attention

The CNN-LSTM with Attention model combines convolutional and recurrent layers. Initially, a Conv1D layer (64 filters, kernel size 3) extracts local features from the SIRI dimensions, which are then fed into an LSTM layer (128 units, return sequences=True) followed by Batch Normalization. The learned features are then combined with the attention-weighted DEMATEL factors. A final Dense layer predicts the priority domain.

The Adam optimizer, a stochastic gradient descent method based on adaptive moments, was chosen to train the neural network due to its ability to utilize varying adaptive learning rates [19]. Combining the advantages of AdaGrad and RMSProp, Adam maintains an adaptive learning rate for each parameter by calculating moving averages of the first and second gradient moments. The learning rate was initially set to 0.001, enabling the network to retain optimal weight management at the conclusion of each batch by appropriately updating its parameters and regulating the learning speed of the model. The ReLU (Rectified Linear Unit) activation function was employed, outputting positive inputs directly while outputting zero otherwise, thereby addressing the leaky gradient issue and enhancing model learning and function. For multiclass classification, the Softmax function was used as the activation function in the output layer to predict a multinomial probability distribution. To determine the best hyperparameter combination for validation performance, a multi-step tuning process was employed. Finally, evaluating performance by accuracy enabled conclusions regarding the efficiency of our network's performance. As previously discussed, the greatest outcomes were achieved using the hyperparameter combinations.

4.2 Evaluation of the neural network-based models

A key indicator of overfitting is an increase in validation error. To rigorously assess the performance of our network models, we selected several popular criteria relevant to our multiclass classification task: Categorical Cross Entropy (CCE), Precision, Recall, and F1 Score [20]. Our model leverages CCE to learn to assign high probabilities to correct digits and low probability to incorrect ones. Furthermore, precision, which is directly proportional to model efficiency, evaluates the model's accuracy against real data points [20]. Ideally, the best neural network will exhibit low CCE and high accuracy.

Figures 3, 4, and 5 compare and illustrate the evolution of CCE and accuracy as a function of training epochs for the three outputs (Process Priority, Technology Priority, and Organization Priority) for each of our three models:

- **Organizational priority**

✓ CNN with attention: Training Accuracy increases rapidly early on, then continues to increase more slowly to a plateau around 89% after about 100 epochs. Training Loss decreases rapidly and continues to decrease to near 0.2.

✓ RNN with attention: Training Accuracy increases rapidly early on, then continues to increase more slowly to a plateau around 90% after about 80 epochs. Training Loss decreases rapidly and continues to decrease to near 0.2.

✓ CNN-LSTM with attention: Training Accuracy increases rapidly early on, then continues to increase more slowly to a plateau around 90% after about 85 epochs. Training Loss decreases rapidly and continues to decrease to near 0.2.

- **Process priority**

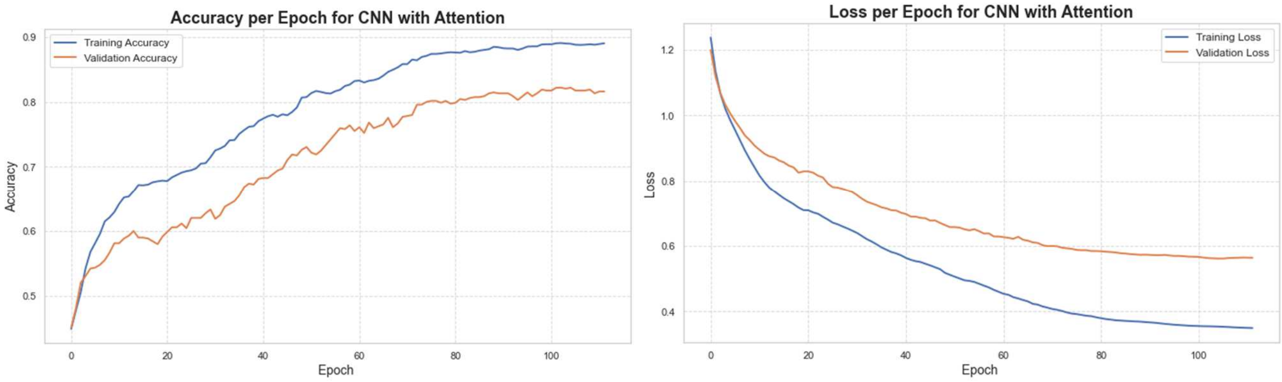
✓ CNN with attention: Training Accuracy increases rapidly early on, then continues to increase more slowly to a plateau around 80% after about 100 epochs. Training Loss decreases rapidly and continues to decrease to near 0.2.

✓ RNN with attention: Training Accuracy increases rapidly early on, then continues to increase more slowly to a plateau around 85%. Training Loss decreases rapidly and continues to decrease to near 0.2.

- ✓ CNN-LSTM with attention: Training Accuracy increases rapidly early on, then continues to increase more slowly to a plateau around 90% after about 150 epochs. Training Loss decreases rapidly and continues to decrease to near 0.15.

- **Technology priority**
- ✓ CNN with attention: Training Accuracy increases rapidly early on, then continues to increase more slowly to a plateau around 95% after about 150 epochs. Training Loss decreases rapidly and continues to decrease to near 0.15.
- ✓ RNN with attention: Training Accuracy increases rapidly early on, then continues to increase more slowly to a plateau around 93% after about 140 epochs. Training Loss decreases rapidly and continues to decrease to near 0.2.
- ✓ CNN-LSTM with attention: Training Accuracy increases rapidly early on, then continues to increase more slowly to a plateau around 97% after about 150 epochs. Training Loss decreases rapidly and continues to decrease to near 0.15.

a)



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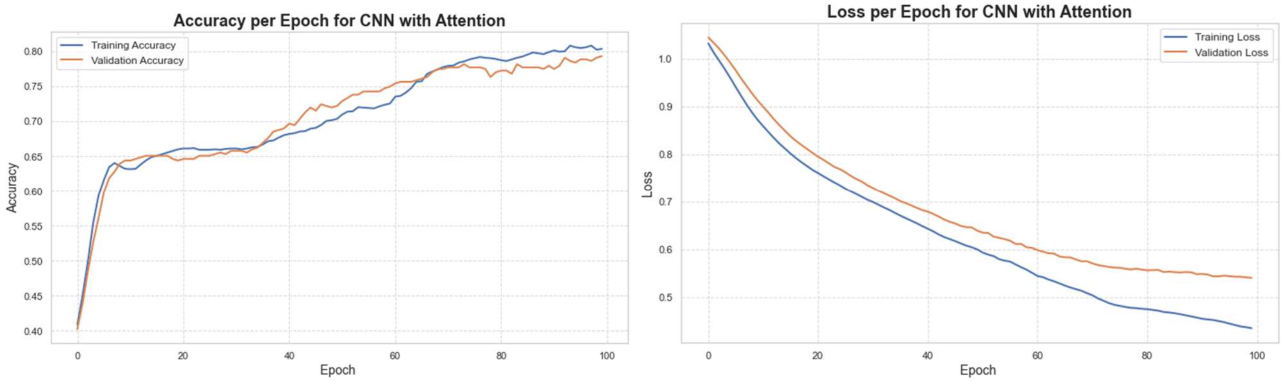

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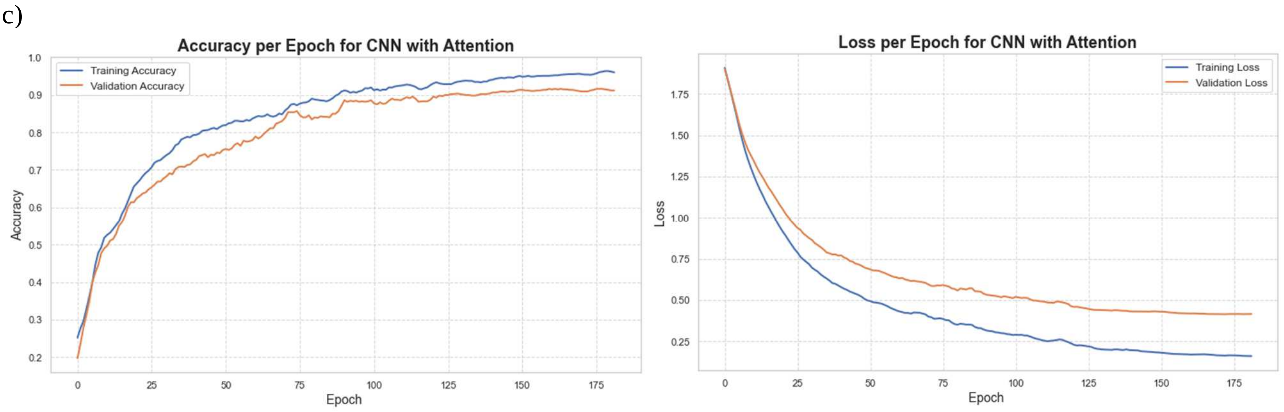
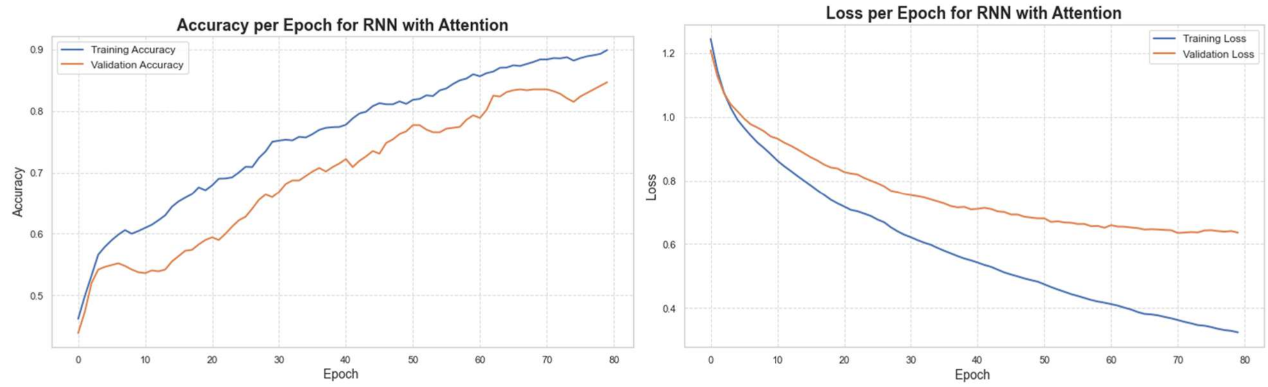
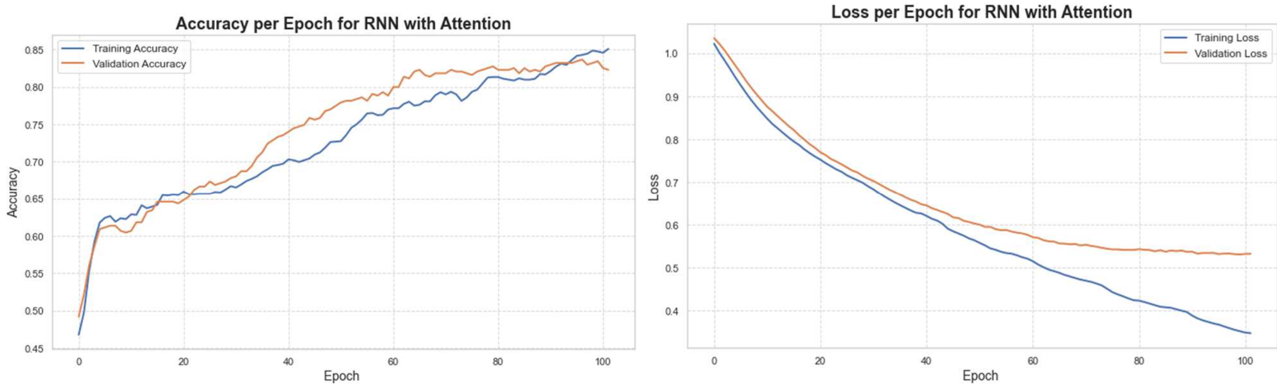


Figure 3 CNN Training curves: CCE Loss and accuracy vs. Epochs for Priority: a) Organizational priority, b) Process priority, c) Technology priority

d)



e)



f)

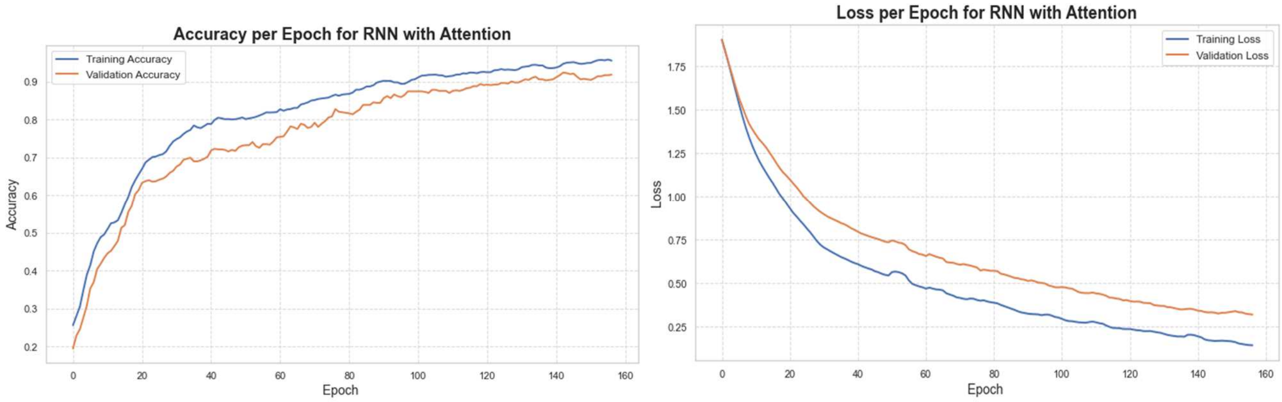
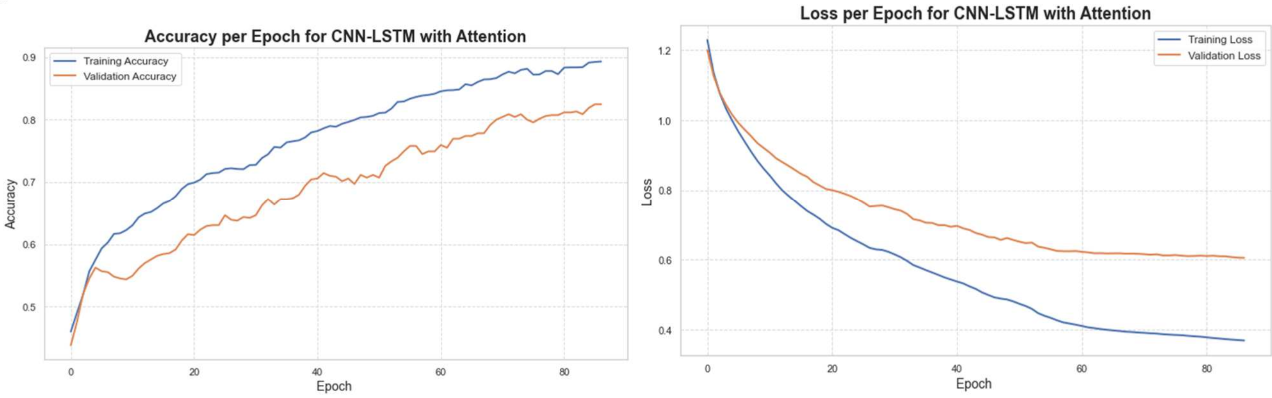
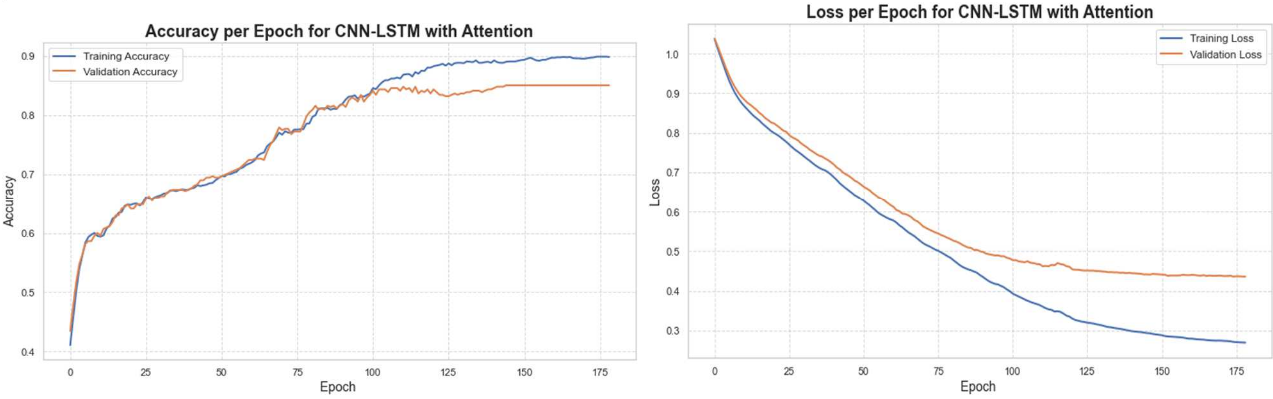


Figure 4 RNN Training curves: CCE Loss and accuracy vs. Epochs for Priority: d) Organizational priority, e) Process priority, f) Technology priority

g)



h)



i)

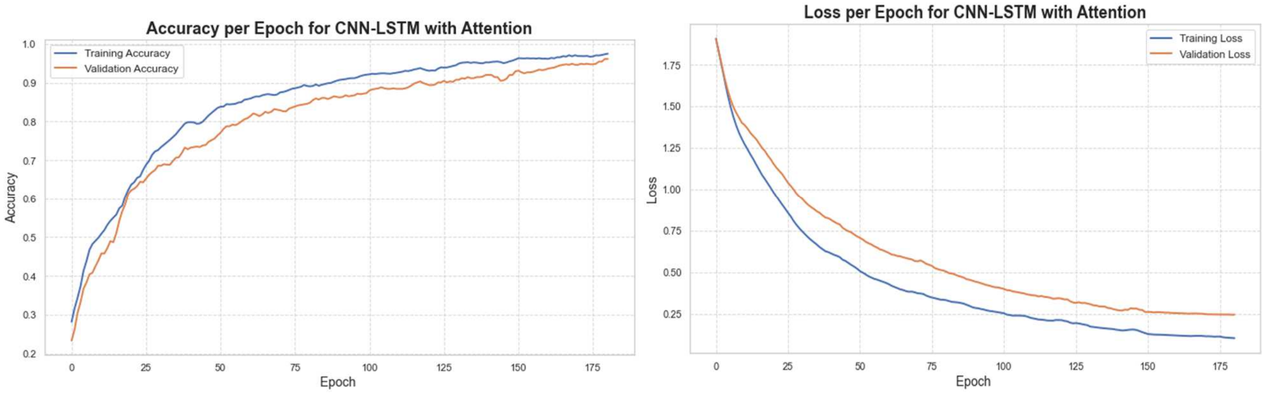


Figure 5 CNN-LSTM Training curves: CCE Loss and accuracy vs. Epochs for priority: g) Organizational priority, h) Process priority, i) Technology priority

For our models, 500 epochs were proposed as sufficient for all three outputs, yielding smoother graphs and high accuracy, reaching up to 97%. Overall, the CNN with Attention, RNN with Attention, and CNN-LSTM with Attention models demonstrated good performance in predicting the priority domain (Organization, Process, Technology) for Industry 4.0 implementation. However, CNN with Attention model generally exhibited more consistent and robust performance across the three outputs, making it a potentially more reliable choice. The CNN-LSTM with Attention model showed promise for predicting Technology Priority specifically, while the RNN with Attention model was more prone to overfitting and seemed less reliable.

In addition to classification accuracy, four measures are generally required to evaluate a neural network model's performance based on a test dataset: Test Loss (a lower measure of error is better), Accuracy (a higher percentage of correctly classified examples is better), Precision (the model's ability to avoid labeling an instance as positive that is actually negative, meaning a low false positive rate), Recall (the model's ability to find all positive instances, meaning a low false negative rate), and F1 Score (the harmonic mean of precision and recall, which provides a balanced measure of the model's accuracy) results are shown in Tables 2, 3, and 4.

Despite the performance, and like the previous models, the CNN-LSTM with Attention model tends to perform best, but the choice of model depends on the specific priority domain. The models are significantly better at predicting Technology Priority than Process or Organization Priority, suggesting that the factors influencing technology are more easily captured. The models all need improvement but are a good starting point. To have the best model overall, we would suggest using the CNN-LSTM with Attention model.
In summary, the bias and weights were initially chosen at random; subsequently, the neural network will learn on its own through the application of multiple iterations, performing forward propagation while tagging the measures highlighted in this session.

Table 2 Performance indicators of the neural network with self-attention-based models for predicting Organization priority

Model	Test Loss	Test Accuracy	Precision	Recall	F1 Score
CNN with self-attention	0.43	77.7%	77.8%	77.7%	77.3%
RNN with Attention	0.54	84.3%	85.9%	84.3%	83.8%
CNN-LSTM with Attention	0.55	84.3	84.8%	84.3%	83.7%

Table 3 Performance indicators of the neural network with self-attention-based models for predicting Process priority

Model	Test Loss	Test Accuracy	Precision	Recall	F1 Score
CNN with self-attention	0.43	77.7%	77.8%	77.7%	77.3%
RNN with Attention	0.44	82.4%	82.5%	82.4%	82.03%
CNN-LSTM with Attention	0.42	83.3%	85.5%	83.3%	82.6%

Table 4 Performance indicators of the neural network with self-attention-based models for predicting Technology priority

Model	Test Loss	Test Accuracy	Precision	Recall	F1 Score
CNN with self-attention	0.36	92.8%	92.8%	92.8%	92.2%
RNN with Attention	0.31	87.8%	87.7%	87.8%	87.4%
CNN-LSTM with Attention	0.26	93.3%	93.1%	93.3%	92.9%

5 Conclusion

Based on these observations, this paper presents a decision support tool that reliably and simultaneously determines the appropriate priority and the maturity of the SIRI dimensions for each case. Establishing a relationship between input variables (company size, SIRI dimensions, and CSF maturity) and neural network-based models was used due to the complexity of the output variables (priority of focus areas). Therefore, a trustworthy database of training and validation data was established and used to train models, refined through analysis of several neural network hyperparameters and the best combination described. The CNN-LSTM with Attention model generally performed best, although the optimal choice depends on the specific priority domain being targeted.

Performance evaluation details were presented for each output. High dependability and positive outcomes highlight the models' value as an outstanding method for solving the complex problem of deciding on a suitable focus area priority for improving Industry 4.0 maturity, based on the initial maturity and the company size.

Our study provides clothing and textile industries with a means to address the intense discussion over priorities, using standard technology and a single language. The model provides clothing managers with recommendations for successfully implementing Industry 4.0 technologies, optimizing quality, time, and resources. This generic approach can be used by any business looking to thrive in its Industry 4.0 implementation journey, and the methodology can be extended to any context and any condition.

For future research, first, similar studies can be conducted in different settings to confirm the generalization of the results. Secondly, the findings of this study could serve as a starting point for other researchers to create a roadmap for successful digital transformation by developing initiatives tailored to each priority focus area.

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