Convolutional Interval-Valued Neutrosophic Network for Intelligent Evaluation of Smart Clothing Design Choices

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Abstract—Smart clothing design turned out to be a set of complex decision-making processes requiring complementary aesthetics, functionality, as well as customer preferences. This, in turn, makes the traditional evaluation methods struggle to deal with uncertainty and subjectivity in customer feedback about smart clothing design. In an attempt to address this challenge, this research article proposes a novel Neutrosophic approach that integrates Interval-Valued Neutrosophic (IVN) with Convolutional Network to build an intelligent tool for the evaluation of smart clothing design choices. The Neutrosophic representation enables modeling uncertainty, inconsistency, and hesitancy in decision-making by assigning interval-ed membership degrees for different views of smart clothes design. Using the interval-valued representations, we enable robust learning and interpretation of user partialities while handling vague feedback. Proof of concept experiments are conducted on a case study for a smart fashion dataset, and the quantitative results and analysis demonstrate that the proposed approach outperforms the standard techniques for smart clothes classification and ranking design choices. The findings from this analysis prove the ability of our approach to facilitate intelligent decision support in the fashion industry.

Keywords: Neutrosophic theory, Interval-Valued Neutrosophic (IVN), Smart Clothing, Neutrosophic Intelligence.

1. Introduction

The integration of artificial intelligence (AI) in fashion design has revolutionized the way designers and consumers evaluate clothing choices [1]. The design of smart clothing is a complicated process that entails advanced materials and embedded technologies and requires intelligent decision-making frameworks that balance aesthetics, functionality, and user preferences [2]. Nevertheless, the task of evaluating smart clothing designs and making appropriate choices persists as characteristically subjective and uncertain, as customer feedbacks always differ according to different factors such as comfort, style, and usability [3]. This in turn makes the standard evaluation techniques hard to consider for this kind of uncertainty causing inconsistency or biased evaluations.

The neutrosophic sets (NS) were proposed by Smarandache [4] as a mathematical model extending the original concept of fuzzy logic to handle inconsistency, uncertainty, and impreciseness inherent in different life sectors. They designed NS based on a neutrality degree that was presented as a new and autonomous component not exist in fuzzy logic [5], [6]. Thereby, NS can be defined by three membership components which are truth, indeterminacy, and falsity. With the integration of indeterminacy components, we can allow a more detailed description of membership, facilitating the application of NS in decision-making. Accordingly, Neutrosophic theory can be very valuable for clothes designers to differentiate between complete truth and partial truth or between complete untruth and partial falsehood in their work. This can be achieved through systematic comparison between diverse kinds of membership. This qualifies the NS to have acted as an assistive tool for either human or AI decisions to handle the inherent levels of uncertainty within the smart clothes industry [7]. Recently, there is several categories of NS have been proposed in different publications. Trapezoidal NS (TNS) [8], interval-valued NS (IVNSs) [9], multi-valued NSs (MVNs) [10], single-valued NSs (SVNSs) [11], [12], and Intuitionistic NS [13] are some types of these NSs [14].

This research proposes a Convolutional Interval-Valued Neutrosophic Network for the intelligent evaluation and categorization of smart clothing design choices. Instead of scalar membership for truth (T), indeterminacy (I), and falsity (F) components, IVN theory extends original NS by offering intervals of values, which allows a more nuanced representation of uncertainty and disinclination in decision-making. Our framework develops an IVN encoding module to transform the clothes images into IVN-embedding. Then, we pass the IVN embedding to stacked convolutional kernels to learn discriminatory patterns from the IVN components. By the end of the model, we propose an improved IVN loss function to update the gradients of the model according to a decision made by three components.

The remainder of this paper is structured as follows: Section 2 presents the preliminaries and mathematical definitions of IVN operations, Section 3 outlines the case study and the proposed IVN framework, Section 4 discusses the results, and Section 5 concludes the findings.

2. Foundational Concepts

Definition 1. Neutrosophic set [4] to extend the fuzzy set for modeling uncertainty, and is defined as:

$$A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle : x \in U\} \tag{1}$$

$$0^- \leq \mathrm{T_A(x)} + \mathrm{I_A(x)} + \mathrm{F_A(x)} \leq 3^+ \tag{2}$$

$$\mathrm{T_A}: \mathrm{X} \to]^-0,1[^+, \quad \mathrm{I_A}: \mathrm{X} \to]^-0,1[^+, \quad \mathrm{F_A}: \mathrm{X} \to]^-0,1[^+ \tag{3}$$

Definition 2. An IVNS redefine the membership of each component to be interval instead of scalars, which can be expressed as:

$$A = \{\langle x, [T_L(x), T_U(x)], [I_L(x), I_U(x)], [F_L(x), F_U(x)]\rangle : x \in U\} \tag{4}$$

where the constituting intervals satisfy the following condition:

$$T_L(x) + I_L(x) + F_L(x) \leq 3,\ T_U(x) + I_U(x) + F_U(x) \leq 3 \tag{5}$$

In the above formula, $T_L(x)$ and $T_U(x)$ denote the lower and upper bounds of the truth membership, and similarly for I and F.

Definition 3. Given two IVNSs A and B, the union $A \cup B$ is defined as:

$$A \cup B = \left\{\left\langle \begin{matrix} x, \left[\max\left(T_L^A(x), T_L^B(x)\right), \max\left(T_U^A(x), T_U^B(x)\right)\right], \\ \left[\min\left(I_L^A(x), I_L^B(x)\right), \min\left(I_U^A(x), I_U^B(x)\right)\right], \\ \left[\min\left(F_L^A(x), F_L^B(x)\right), \min\left(F_U^A(x), F_U^B(x)\right)\right] \end{matrix} \right\rangle : x \in U \right\} \tag{6}$$

Definition 4. Given two IVNSs A and B, the intersection $A \cap B$ is defined as:

$$A \cap B = \left\{\left\langle \begin{matrix} x, \left[\min\left(T_L^A(x), T_L^B(x)\right), \min\left(T_U^A(x), T_U^B(x)\right)\right], \\ \left[\max\left(I_L^A(x), I_L^B(x)\right), \max\left(I_U^A(x), I_U^B(x)\right)\right], \\ \left[\max\left(F_L^A(x), F_L^B(x)\right), \max\left(F_U^A(x), F_U^B(x)\right)\right] \end{matrix} \right\rangle : x \in U \right\} \tag{7}$$

Definition 5. Given an IVNSs $A = \left\{\left\langle x, \left[T_A^L, T_A^U\right], \left[I_A^L, I_A^U\right], \left[F_A^L, F_A^U\right]\right\rangle : x \in U\right\}$, then the complement A^c can be expressed as:

$$A^c = \left\{\left\langle x, \left[F_A^L, F_A^U\right], \left[1 - I_A^L, 1 - I_A^U\right], \left[T_A^L, T_A^U\right]\right\rangle : x \in U\right\} \tag{8}$$

Definition 6. Given two IVNSs $A = \left\{\left\langle x, \left[T_A^L, T_A^U\right], \left[I_A^L, I_A^U\right], \left[F_A^L, F_A^U\right]\right\rangle : x \in U\right\}$, and $B = \left\{\left\langle x, \left[T_B^L, T_B^U\right], \left[I_B^L, I_B^U\right], \left[F_B^L, F_B^U\right]\right\rangle : x \in U\right\}$, the following relations apply as follows:

(9)

$$A \subseteq B \; iff \; T_A^L \le T_B^L, T_A^U \le T_B^U; I_A^L \ge I_B^L, I_A^U \ge I_B^U; F_A^L \ge F_B^L, F_A^U \ge F_B^U$$

$$A = B \; if \; and \; only \; if \; A \subseteq B \; and \; B \subseteq A. \tag{10}$$

Definition 7. Given an IVNS $A = \{\langle x, [T_A^L, T_A^U], [I_A^L, I_A^U], [F_A^L, F_A^U]\rangle : x \in U\}$,we can compute the score and accuracy functions as follows:

$$S_A(x) = [T_A^L + 1 - I_A^U + 1 - F_A^U, T_A^U + 1 - I_A^L + 1 - F_A^U]. \tag{11}$$

$$a_A(x) = [min\{T_A^L - F_A^L, T_A^U - F_A^U\}, max\{T_A^L - F_A^L, T_A^U - F_A^U\}] \tag{12}$$

Definition 8. Given two IVNSs $A = \{\langle x, [T_A^L, T_A^U], [I_A^L, I_A^U], [F_A^L, F_A^U]\rangle : x \in U\}$, and $B = \{\langle x, [T_B^L, T_B^U], [I_B^L, I_B^U], [F_B^L, F_B^U]\rangle : x \in U\}$,there are many elementary operations on to be applied:

- Addition

$$A \oplus B = \left\{\left\langle \begin{matrix} x, [T_A^L + T_B^L - T_A^L \cdot T_B^L, T_A^U + T_B^U - T_A^U \cdot T_B^U], \\ [I_A^L \cdot I_B^L, I_A^U \cdot I_B^U], \\ [F_A^L \cdot F_B^L, F_A^U \cdot F_B^U] \end{matrix} \right\rangle : x \in U \right\} \tag{13}$$

- Subtraction

$$A \ominus B = \left\{\left\langle \begin{matrix} x, [T_A^L - T_B^L, T_A^U - T_B^U], \\ [\max(I_A^L, I_B^L), \max(I_A^U, I_B^U)], \\ [F_A^L - F_B^L, F_A^U - F_B^U] \end{matrix} \right\rangle : x \in U \right\} \tag{14}$$

- Multiplication

$$A \otimes B = \left\{\left\langle \begin{matrix} x, [T_A^L \cdot T_B^L, T_A^U \cdot T_B^U], \\ [I_A^L + I_B^L - I_A^L \cdot I_B^L, I_A^U + I_B^U - I_A^U \cdot I_B^U], \\ [F_A^L + F_B^L - F_A^L \cdot F_B^L, F_A^U + F_B^U - F_A^U \cdot F_B^U] \end{matrix} \right\rangle : x \in U \right\} \tag{15}$$

- Scalar multiplications

$$\lambda A = \left\{\left\langle \begin{matrix} x, [1 - (1 - T_A^L)^\lambda, 1 - (1 - T_A^U)^\lambda], \\ [(I_A^U)^\lambda, (I_B^U)^\lambda], \\ [(F_A^U)^\lambda, (F_B^U)^\lambda] \end{matrix} \right\rangle : x \in U \right\} \tag{16}$$

- Power

$$A^\lambda = \left\{\left\langle \begin{matrix} x, [(T_A^L)^\lambda, (T_A^U)^\lambda], \\ [1 - (1 - T_A^U)^\lambda, 1 - (1 - T_B^U)^\lambda], \\ [1 - (1 - F_A^U)^\lambda, 1 - (1 - F_B^U)^\lambda] \end{matrix} \right\rangle : x \in U \right\} \tag{17}$$

Definition 9. Given an IVN $A = [T_A^L, T_A^U], [I_A^L, I_A^U], [F_A^L, F_A^U]$, the deneutrosophication can be computed as follows:

$$\mathfrak{D}(A) = \left(\frac{\left(T_A^L + T_A^U\right)}{2} + \left(1 - \frac{\left(I_A^L + I_A^U\right)}{2}\right)\left(I_A^U\right) - \left(\frac{\left(F_A^L + F_A^U\right)}{2}\right)\left(1 - F_A^U\right) \right) \quad (18)$$

Definition 10. Given a set of IVNSs $A_j = \left\{\left\langle x, \left[T_{A_j}^L, T_{A_j}^U\right], \left[I_{A_j}^L, I_{A_j}^U\right], \left[F_{A_j}^L, F_{A_j}^U\right]\right\rangle : x \in U\right\}$, and corresponding weight vector $W = (w_1, w_2, \dots, w_n)^T$, where $w_j \geq 0$, and $\sum w_j = \mathbf{1}$. Their general weighted aggregation function is formulated as follows:

$$Z = IVNS\text{GWA}(A_1, A_2, \dots, A_n) = \left(\sum_{j=1}^{n} w_j A_j^{\lambda}\right)^{\frac{1}{\lambda}}$$

$$= \left(\sum_{j=1}^{n} w_j \left(\left\langle\left[T_j^{l\,\lambda}, T_j^{r\,\lambda}\right], \left[1-\left(1-I_j^l\right)^{\lambda}, 1-\left(1-I_j^r\right)^{\lambda}\right], \left[1-\left(1-F_j^l\right)^{\lambda}, 1-\left(1-F_j^r\right)^{\lambda}\right]\right\rangle\right)\right)^{\frac{1}{\lambda}}$$

$$= \left(\sum_{j=1}^{n} w_j \left(\left\langle\left[1-\left(1-\left(T_j^L\right)^{\lambda}\right)^{w_j}, 1-\left(1-\left(T_j^U\right)^{\lambda}\right)^{w_j}\right], \left[1-\left(1-\left(I_j^L\right)^{\lambda}\right)^{w_j}, 1 - \left(1-\left(I_j^U\right)^{\lambda}\right)^{w_j}\right], \left[1-\left(1-\left(F_j^L\right)^{\lambda}\right)^{w_j}, 1-\left(1-\left(F_j^U\right)^{\lambda}\right)^{w_j}\right]\right\rangle\right)\right)^{\frac{1}{\lambda}} \quad (19)$$

3. Case Study and Method

This section provides a holistic explanation of the proposed approaches for evaluating and assessing smart clothes design in uncertain and complicated environments. Our discussion begins by explaining the case study we chose to prove the concept of our methodology explaining their relevance to the subject matter.

3.1 Case Study: Fashion-MNIST Dataset

To evaluate the effectiveness of the proposed method in smart clothing design assessment, we utilize the Fashion-MNIST dataset as a case study. Fashion-MNIST is a widely used benchmark dataset designed as an alternative to MNIST, containing 70,000 grayscale images (60,000 for training and 10,000 for testing) of 10 fashion categories. Each image has a resolution of 28×28 pixels and represents various clothing items (refer to Table 1).

Table 1. Class distribution of the Fashion-MNIST dataset

Label	Class Name	# samples
0	T-shirt/top	1000
1	Trouser	1000
2	Pullover	1000
3	Dress	1000

4	Coat	1000
5	Sandal	1000
6	Shirt	1000
7	Sneaker	1000
8	Bag	1000
9	Ankle boot	1000

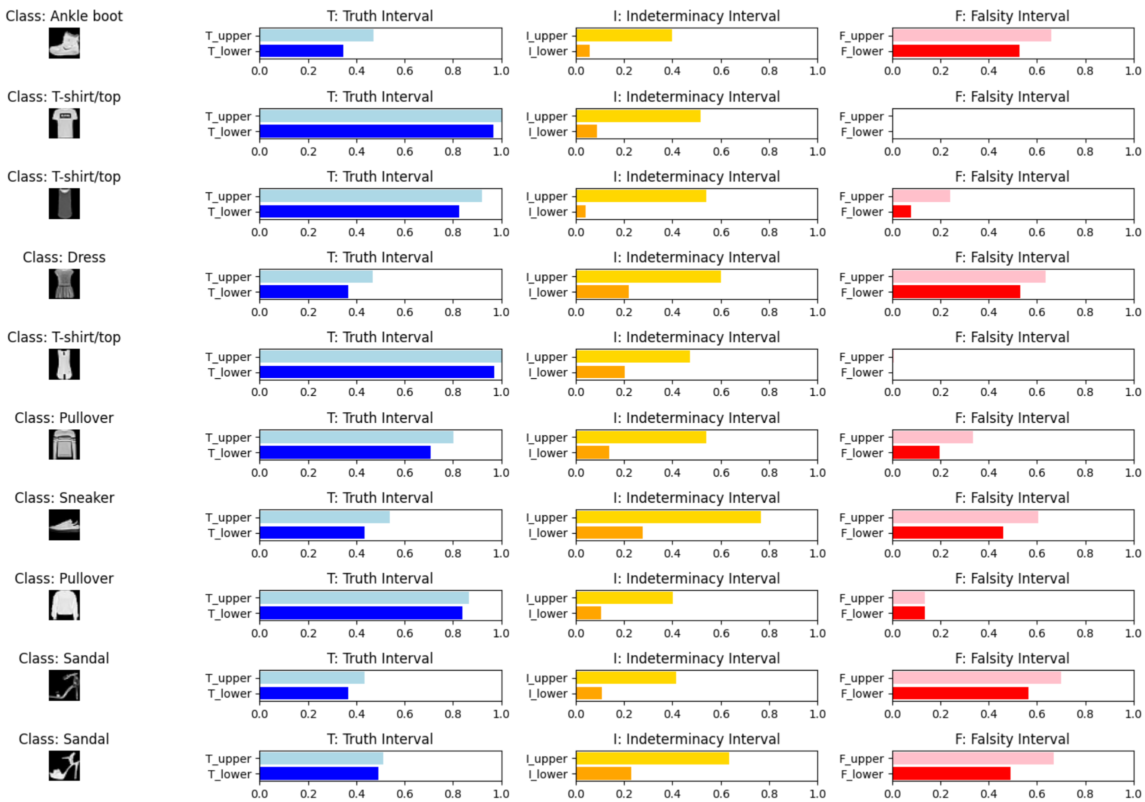

Figure 1. visualization of IVN representation of different fashion images.

The dataset contains diverse clothing items, enabling an initial validation of the model's capability in evaluating design choices. Fashion-MNIST is widely used in ML research, allowing a fair comparison between image classifiers and our IVN-enhanced classifier. While Fashion-MNIST contains simple grayscale images, the approach can be extended to more complex datasets containing high-resolution smart clothing images with additional design attributes.

3.2. Proposed Method

The first step in the proposed method emphasize integrating IVNS into our network to describe how fashion images are embedded into the three IVNS components, as mentioned earlier. Given an input image X, we can extract three interval-valued components: $T = [T_L, T_U]$, $I = [I_L, I_U]$, and $F = [F_L, F_U]$, which are constrained within specific intervals as given below:

$$\begin{gathered} 0 \le T_L \le T_U \le 1 \\ 0 \le I_L \le I_U \le 1 \\ 0 \le F_L \le F_U \le 1 \\ T_U + I_U + F_U \le 3 \end{gathered} \tag{20}$$

To do so, we can extract expressive statistical features fusing stacked convolutional layers. These features are later distorted into IVNS components using mathematical encoding scheme (refer to Figure 1).

In our design, T should reflects powerful to which image belongs to a particular class. To do so, we apply a feature extraction function. $\phi_i(X)$, namely stack of convolution layers with activation layers, as shown in Figure 2.

$$\begin{aligned} T_L &= \sigma\left(\frac{1}{n}\sum_{i=1}^{n} \phi_i(X) - \alpha_T\right) \\ T_U &= \sigma\left(\frac{1}{n}\sum_{i=1}^{n} \phi_i(X) + \alpha_T\right) \end{aligned} \tag{21}$$

where $\phi(X)$ symbolizes feature vector extracted from the convolution layers, n is the number of feature values, $\sigma(x) = \frac{1}{1+e^{-z}}$ symbolizes the sigmoid function, and α_T symbolizes a small adjustment factor.

Next, in our design, the uncertainty in learning is often caused by noise, occlusion, or resemblance to manifold classes.

$$\begin{aligned} I_L &= \sigma\left(\frac{1}{n}\sum_{i=1}^{n} \left|\phi_i(X) - \mu_\phi(X)\right| - \alpha_I\right) \\ I_U &= \sigma\left(\frac{1}{n}\sum_{i=1}^{n} \left|\phi_i(X) - \mu_\phi(X)\right| + \alpha_I\right) \end{aligned} \tag{22}$$

Moreover, the falsity degree account for level to which an image does not belong to the target class. We compute this based on the distance from the prototype vector of the class:

$$\begin{aligned} F_L &= \sigma(d(X, C) - \alpha_F) \\ F_U &= \sigma(d(X, C) + \alpha_F) \end{aligned} \tag{23}$$

where $d(X, C)$ symbolizes Manhattan distance function. It is computed as:

$$d(X, C) = \frac{1}{n}\sum_{i=1}^{n} \left|\phi_i(X) - C_i\right| \tag{24}$$

where C_i symbolizes the class-centroid computed over all clothes images. α_F symbolize interval adjustment factor.

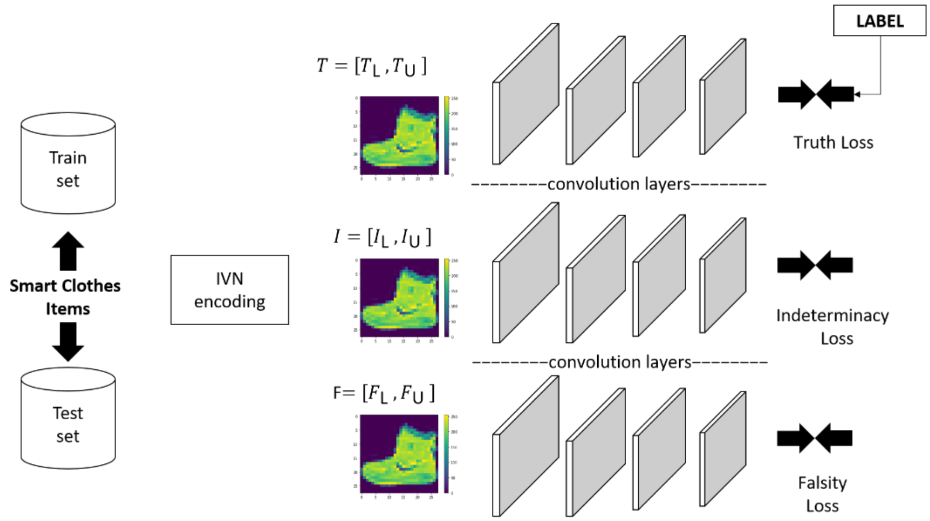

Figure 2. illustration of the architecture of the proposed approach

To train the proposed approach on smart clothing items, we propose and develop an objective function for minimizing the error for all three components. This function is inspired by the interval nature of IVNSs. Assume having an instance i with ground truth intervals are $[T_i^{\mathrm{gt}}, I_i^{\mathrm{gt}}, F_i^{\mathrm{gt}}]$, while the prediction intervals are $\left[T_i^{\mathrm{pred}}, I_i^{\mathrm{pred}}, F_i^{\mathrm{pred}}\right]$, then we can formulate the loss can as follows:

$$\mathcal{L}_{\mathrm{IVNS}} = \sum_{i=1}^{N} \left(\underbrace{\mathcal{L}_{\mathrm{T}}\left(T_i^{\mathrm{gt}}, T_i^{\mathrm{pred}}\right)}_{\text{Truth Loss}} + \underbrace{\mathcal{L}_{\mathrm{I}}\left(I_i^{\mathrm{gt}}, I_i^{\mathrm{pred}}\right)}_{\text{Indeterminacy Loss}} + \underbrace{\mathcal{L}_{\mathrm{F}}\left(F_i^{\mathrm{gt}}, F_i^{\mathrm{pred}}\right)}_{\text{Falsity Loss}} \right), \tag{25}$$

Where $\mathcal{L}_{\mathrm{T}}, \mathcal{L}_{\mathrm{I}}$ and $\mathcal{L}_{\mathrm{F}}$ represent the interval mean squared error (IMSE) that is calculated as follows:

$$\mathcal{L}_T = \frac{1}{2}\left(\left(T_L^{pred} - T_L^{gt}\right)^2 + \left(T_U^{pred} - T_U^{gt}\right)^2\right), \tag{26}$$

We account for ensuring that the intervals remain valid such that $T_{\mathrm{L}} \leq T_{\mathrm{U}}$, $I_{\mathrm{L}} \leq I_{\mathrm{U}}$, and $F_{\mathrm{L}} \leq F_{\mathrm{U}}$.

$$\mathcal{L}_{penalty} = \sum_{i=1}^{N} \left(max(0, T_L - T_U) + max(0, I_L - I_U) + max(0, F_L - F_U)\right) \tag{27}$$

4. Results and discussions

Herein, we introduce and analyze the experimental results from the proposed method to be applied for evaluating smart clothing items. We emphases on the effectiveness of coupling the IVN representation to enhance the classification performance, handling uncertainty, and improve the decision-making in smart clothing design assessment.

Table 2. Quantitative results against competing methods.

Metric	Proposed	DT	RF
Accuracy	88.26	51.27	87.64
F1-score	88.28	40.37	87.49
Precision	88.53	35.70	87.53
Recall	88.26	51.27	87.64

In Table 2, we provide comparison between the results of our proposed method against the state of-the art approaches namely decision tree (DT), and random forest (RF). Our comparisons emphasize different performance metrics, namely accuracy, precision, recall, F1-score. These metrics are calculated as follows:

As shown, the tabulated results explain the ability of IVN-CNN model to outperforms traditional classifiers across all evaluation criteria, predominantly in modeling uncertainty in images of smart clothes. In addition, the proposed approach can generalize well to unseen smart clothes, which means reducing misclassification errors. This can over an improved interpretability in smart clothing design valuation.

$$Accuracy[\%] = \frac{TP_j+TN_j}{TP_j+TN_j+FP_j+FN_j} = \frac{\sum_{j=1}^{N_C} M_{j,j}}{\sum_{j=1}^{N_C} \sum_{i=1}^{N_C} M_{i,j}} \cdot 100\%. \tag{28}$$

$$Recall_i[\%] = \frac{TP_i}{TP_i+FN_i} = \frac{M_{i,i}}{\sum_{j=1}^{N_C} M_{i,j}} \cdot 100\% \tag{29}$$

$$Precision_j[\%] = \frac{TP_j}{TP_j+FP_j} = \frac{M_{j,j}}{\sum_{i=1}^{N_C} M_{i,j}} \cdot 100\%, \tag{30}$$

$$F1_{binary} = \frac{TP}{TP+\frac{1}{2}(FN+FP)} \quad (31)$$

To ensure the stability of learning performance on IVN-represented images of smart clothes, we display he progression of training and validation accuracy and loss curves of the models in Figure 3. It could be seen that the curves provide insights into the model's learning behavior, convergence rate, and generalization capability. Also, it is notable that the proposed model achieves stable training process, which means rapid convergence and lower validation loss. This can be attributed to the effect of IVN encoding in mitigating the effects of uncertainty, which means reducing overfitting and increase of robustness. Besides, there is small gap between training and validation, which indicate that model can

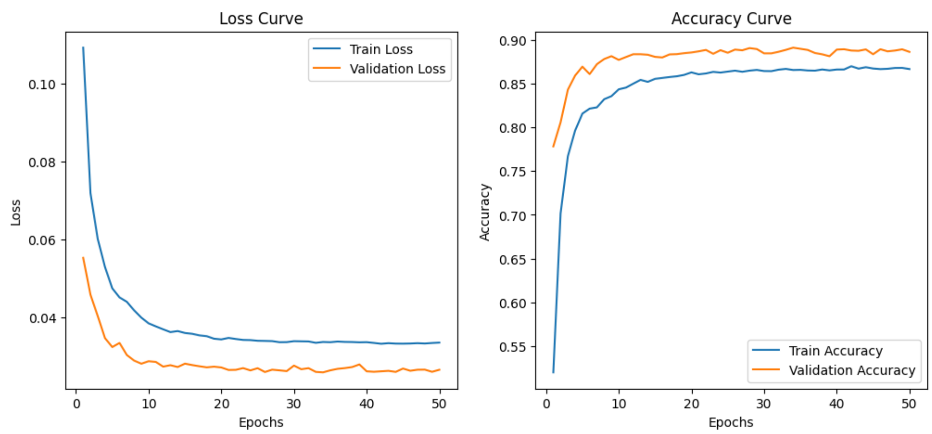

Figure 3. illustration of the learning history of the proposed approach

generalize well due its ability to handle the ambiguous patterns in the images of smart clothes.

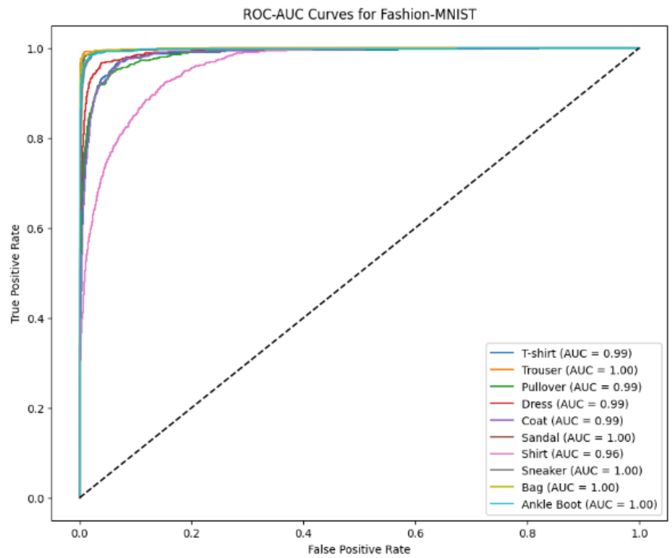

Figure 4. illustration of the ROCAUC curves for the proposed approach

Again, in in Figure 4, we display the trade-off between true positive rate (TPR) and false positive rate (FPR) across diverse clothes classification thresholds, which are encapsulated in form ROC- area under the curve (AUC) curves. This plot provides a fundamental indicator of the model's ability to differentiate between different fashion categories in the images of clothes. It is notable that the IVN-CNN dependably attains a higher AUC score, which demonstrate superior capability to discriminate between overlapping or visually alike clothing items.

In Figure 4, we plot the confusion matrices for the proposed method to provide a detailed breakdown of classification performance across different categories of smart clothes. Each

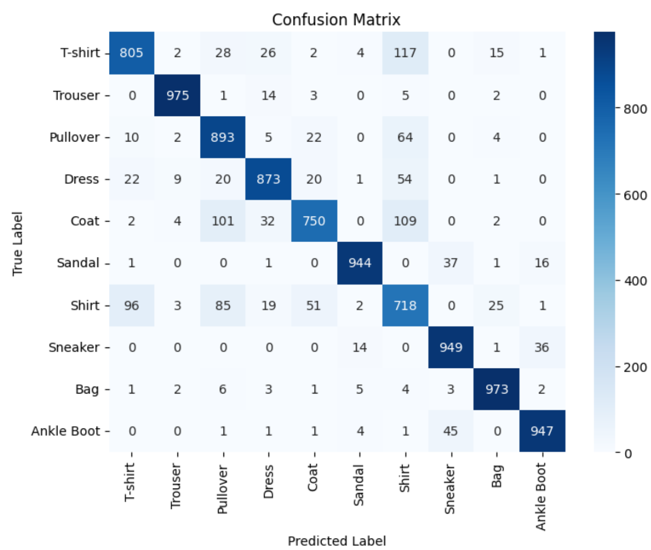

Figure 5. illustration of the confusion matrix of the proposed approach

matrix visualizes the number of correctly and incorrectly classified instances, offering insights into model accuracy and misclassification patterns. As observed, our method achieves a higher number of correct predictions and demonstrates a lower misclassification rate compared to the conventional CNN. Notably, the proposed method reduces confusion between overlapping categories, such as shirts and t-shirts or sneakers and ankle boots, leading to improved classification reliability.

5. Conclusion

In this work, we proposed a Neutrosophic approach that integrates the power of convolutional feature extractors with the uncertainty modeling power of IVN the neutrosophic to obtain improved evaluations of smart clothes design. Our approach extends the conventional convolution architecture to learn to estimate truth, indeterminacy, and falsity membership intervals as an output. We introduce neutrosophic loss function, our approach effectively captures uncertainty and improves decision reliability hence improving the overall gradient update of models. Experimental results demonstrate the potential of our approach in dealing with ambiguous data while making it a promising direction for applications requiring robust classification under uncertainty.

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