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Evaluation of Electrical Properties and Uniformity of Single Wall Carbon Nanotube Dip-Coated Conductive Fabrics Using Convolutional Neural Network-Based Image Analysis

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Abstract: This study proposes a convolutional neural network (CNN)-based image analysis method to evaluate the electrical properties and uniformity of conductive fabrics treated with single-walled carbon nanotube (SWCNT) dip-coating. The conductive fabric was produced by dip-coating cotton-blended spandex with SWCNT, and the surface images were scanned and preprocessed to obtain image data, while resistance measurements were conducted to obtain labels and build the dataset. SEM analysis revealed that as the number of dip-coating cycles increased, particle density and path formation improved. The CNN model learned the relationship between surface images and resistance values, achieving a high predictive performance, with an R-squared (R^2) value of 0.9422. The model demonstrated prediction accuracies of 99.1792% for the coefficient of variation (CV) of uniformly coated fabrics and 96.8877% for non-uniformly coated fabrics. Additionally, *p*-value analysis of all fabric samples yielded a result of 0.96044, indicating no statistically significant difference between the predicted and actual values. The proposed CNN-based model can accurately evaluate the electrical uniformity of conductive fabrics, showing potential for contributing to quality control and process optimization in production.

Keywords: smart textile; electrical properties; uniformity analysis; convolutional neural network (CNN); image analysis

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1. Introduction

Conductive fabrics are materials that maintain flexibility while transmitting electrical signals, playing a crucial role in modern electronic textiles. These fabrics impart electrical properties to traditional textile materials, allowing them to perform electrical functions while retaining the same form and texture as conventional clothing and fabrics. Consequently, they provide innovative solutions across various application areas, including medical and health care [1,2], sports and fitness [3], electronic sensors [4], wearable electrodes [5], energy harvesting [6], solar cells [7], EMI shielding [8], and wireless communication [9].

Traditional textile materials such as spandex, cotton, nylon, and polyester serve as the foundation for the fabrication of conductive fabrics. Various techniques are employed to impart conductivity to these conventional textile materials. Notable methods include weaving conductive fibers, such as metal-plated yarns, directly into the fabric [10,11], coating the surface of the fibers with conductive polymers like PEDOT:PSS or metallic nanoparticles [12,13], and utilizing conductive inks for printing applications [14,15]. Among these methods, dip-coating technology stands out due to its simplicity and cost-effectiveness [16,17]. Dip-coating involves immersing the fabric in a solution containing conductive materials and then drying it to impart conductivity. This process is relatively simple, can be implemented without expensive equipment, and is advantageous for large-scale production at low cost, making it highly suitable for commercial applications. In particular, dip-coating with single-walled carbon nanotube (SWCNT) has been widely adopted as an effective technique, as it imparts high electrical conductivity to the fabric while maintaining its lightweight and flexible properties [18,19].

An important aspect of the dip-coating method in the production of conductive fabrics is that the uniform distribution of conductive materials plays a critical role in optimizing electrical performance and stability. The uniformity of resistance in electronic products such as conductive fabrics is critical to their performance and reliability [20–22]. If the conductive materials are not evenly distributed, electrical non-uniformity may arise, leading to fluctuations in electrical resistance. Electrical non-uniformity can result in current concentration, overheating, performance degradation, and reliability issues in devices. In particular, achieving uniform conductivity is crucial for wearable devices, as they remain in close contact with the human body and must operate reliably under various environmental conditions. Consequently, many electronic device manufacturers and researchers strive to achieve uniform conductivity [23–27].

The uniformity of conductive fabrics produced through dip-coating can be evaluated using indicators such as the coefficient of variation (CV). CV is a measure of the variation in data, where a lower CV indicates smaller variation and greater uniformity, while a higher CV indicates larger variation and non-uniformity. Therefore, the CV value of conductive fabrics produced through the dip-coating process serves as an indicator of the product's quality and stability.

Recently, artificial intelligence (AI), a key technological field in the Fourth Industrial Revolution, has gained attention for its applications in regression, prediction, analysis, and evaluation across many areas, thanks to machine learning (ML), which processes complex calculations, and deep learning (DL), which models patterns and correlations through various artificial neural networks [28]. Among these, the convolutional neural network (CNN) is one of the deep learning models primarily used for image recognition and processing [29–31]. It is specifically designed for two-dimensional and three-dimensional data, such as images and videos, making it particularly effective at recognizing and extracting patterns and features from images. Traditional analysis methods require manual feature definition and extraction, which have limitations when analyzing complex patterns or irregular structures. In contrast, CNNs automatically learn and extract features at various levels through multiple layers of filters, effectively recognizing the structure and patterns of fabric surfaces [32,33]. Recent studies have developed systems using CNNs to detect defects or irregularities occurring during fabric dyeing processes. These systems utilize various models, such as visual geometry group networks (VGGNets) and residual networks (ResNets), to accurately detect surface defects in fabrics, demonstrating superior performance compared to traditional manual detection methods [34–39].Through this capability, CNNs can analyze the complex correlations of the electrical properties of conductive textiles produced via the dip-coating method through algorithmic modeling.

In this study, we propose a novel algorithmic method that analyzes the correlation between surface image data and the electrical property of resistance in conductive fabrics through a CNN algorithm and subsequently evaluates the CV rapidly and accurately. To analyze the properties of conductive fabrics produced through SWCNT dip-coating, we developed a CNN model that learns the relationship between resistance and contrast to predict resistance values. By calculating the mean and standard deviation of the predicted resistance values, we designed the method to compute the CV, thereby quantifying the uniformity of the conductive fabrics. The image-based CV evaluation method using CNN proposed in this study enables precise and detailed analysis of the electrical properties of conductive fabrics produced through SWCNT dip-coating and allows for more accurate and efficient quality assessment. In the industrial manufacturing sector, this method is expected to contribute to the optimization and efficiency of industrial processes by enabling the automation of data collection and monitoring processes. Throughout this study, several abbreviations are used; the key abbreviations can be found in Appendix A.

2. Materials and Methods

2.1. Fabric Composition and Conductive Fabric Fabrication

In this study, conductive fabrics were produced based on a material composed of 95% spandex and 5% cotton(Chungage, Daegu, Republic of Korea). Spandex, which is a blend of natural or synthetic rubber and polyurethane fibers, offers both light weight and excellent elasticity and resilience. It returns to its original shape after deformation, ensuring comfortable wear and high durability, which maintains its form through prolonged use and laundering. These properties make spandex widely used in various fields, including clothing, medical supplies, sports equipment, and electronic devices. Spandex fibers, due to their superior mechanical strength and elasticity, can be utilized in fabric sensors through coating and padding processes. Dip-coated conductive fabrics are smooth, flexible, and maintain their elasticity while providing conductivity, making them suitable for various applications and facilitating integration into sensors. Specifically, spandex-based conductive fabrics are well-suited for wearable clothing and devices and are highly useful as electrodes for measuring biological signals. The lightweight and elastic nature of spandex can be effectively employed in applications such as electromyography (EMG) and electrical muscle stimulation (EMS). However, spandex fibers have low moisture absorbency, making it challenging to apply conductive solutions through dip-coating. To address this issue, this study used a cotton-blend spandex fabric, which combines spandex with cotton, known for its excellent moisture absorbency and hydrophilicity. The superior moisture absorbency of cotton fibers plays a crucial role in efficiently absorbing and distributing the conductive solution on the fabric surface during the dip-coating process. Additionally, the moisture absorbency of cotton enhances the durability of the dip-coated layer, allowing the conductive layer to remain evenly distributed and stable over time. These characteristics contribute to improving the durability and quality of the fabric during the dip-coating process. Among the methods of imparting conductivity to textiles through the dip-coating process, using water-based SWCNT can significantly enhance the electrical conductivity of textiles. SWCNT is a lightweight and flexible material, and when applied to textiles through dip-coating, it enables the production of conductive fabrics that retain the inherent lightness and flexibility of the textiles while exhibiting excellent conductivity. SWCNT is chemically stable, highly durable, and can easily impart conductivity to fabrics of various weaves. Therefore, in this study, we successfully manufactured conductive fabrics using cotton-blend spandex by interacting with 0.1% water-based SWCNT.

Figure 1 illustrates the process of converting cotton-blend spandex fabric into conductive fabric through dip-coating. To prevent the integration of air bubbles and ensure uniform distribution on the fabric surface, SWCNT ink was stirred using an ultrasonic machine at 1000 rpm for at least 1 h. The cotton-blend fabric was immersed for 1 min in a solution containing 0.1 wt% water-based SWCNT and then passed through a dip padding machine (Daelim Lab, Seoul, Republic of Korea) to effectively absorb the conductive particles into the fabric. Excess moisture was then removed using a double dryer (Daelim Lab, Seoul, Republic of Korea) at a temperature range of 80 °C to 100 °C for 10 min, with the circulation fan set to 1500 rpm. Finally, the fabric was dried at room temperature for 1 h.

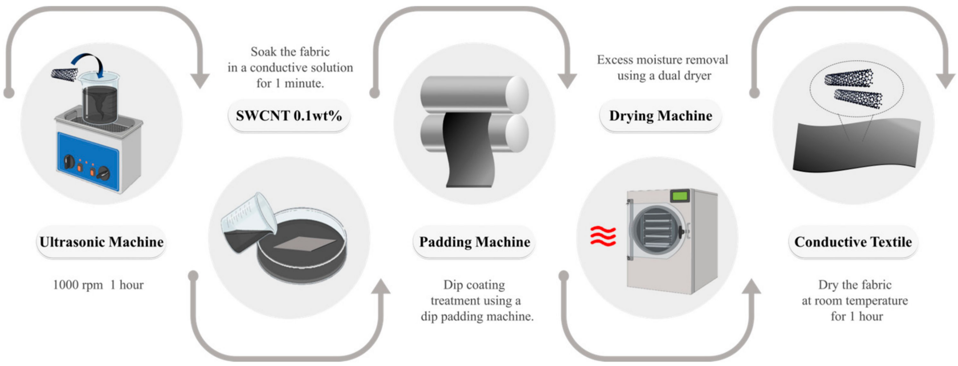


Figure 1. Process of manufacturing conductive fabric.

2.2. Dataset Collection and Processing

Figure 2 visually represents the entire process, from dataset collection to CV evaluation. This figure clearly presents the key stages, including data collection and preprocessing, model training, and CV evaluation, structurally explaining how each stage is interconnected within the overall process leading to the CV evaluation. Accurate data collection is essential for evaluating the electrical performance and uniformity of conductive fabrics using a CNN. To ensure precise model performance and accuracy, the surface images of the fabric must accurately reflect its characteristics. This requires considering appropriate imaging conditions and resolution. Additionally, it is important to collect images under various conditions to ensure the diversity of the dataset. Figure 3 visually illustrates the process of dataset composition for CNN model training.

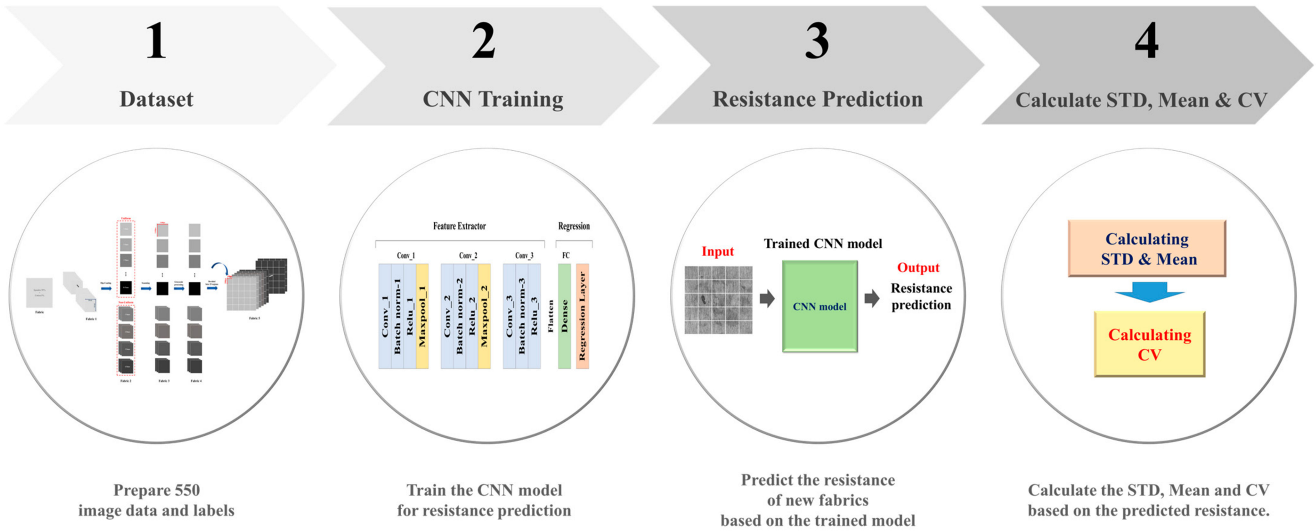


Figure 2. CV evaluation process diagram.

First, a cotton-blend spandex fabric was cut into 10 cm $\times$ 10 cm pieces using a laser cutter, resulting in 22 Fabric 1 samples. To obtain image data under various conditions, 22 conductive fabric samples with different electrical properties were prepared by applying different dip-coating cycles (Fabric 2). Among these, 10 samples were uniformly dip-coated from one to ten times. The remaining 12 samples were dip-coated three, four, five, and six times, with three samples produced for each condition. These were intentionally coated non-uniformly to evaluate electrical uniformity under non-uniform conditions.

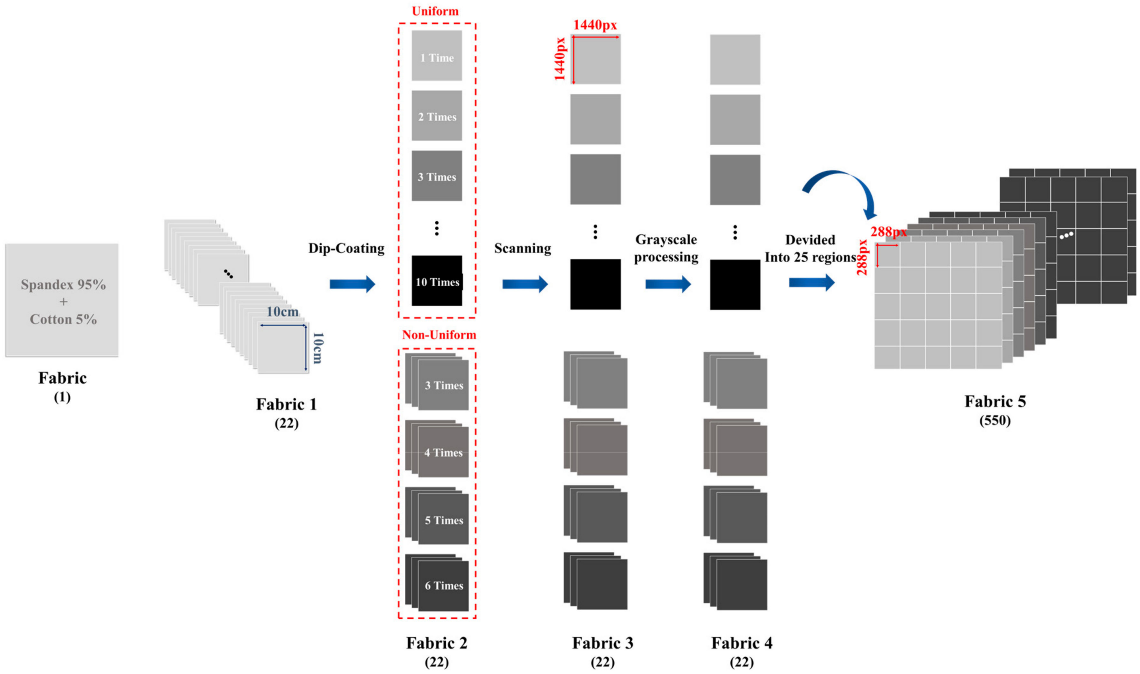


Figure 3. Method for collecting conductive fabric image data for CNN evaluation.

To obtain high-quality and consistent digital images for CNN training, Fabric 3 was scanned using a scanner (Laser Jet Pro MFP M428fdw(HP Development Company, L.P, Palo Alto, CA, USA)), set to 1440 × 1440 pixels with a contrast setting of 100, to minimize distortions from lighting, shadows, and lens effects. This ensured that the digital images accurately reflected the fine details of the conductive fabric. Fabric 3 was subsequently converted to grayscale to produce Fabric 4, which reduced computational complexity and enhanced model training performance.

The quality and quantity of data are critical for CNN model training performance. To augment the dataset, Fabric 4 was divided into 25 sections of 288 × 288 pixels each using MATLAB. Direct cutting of the conductive fabric using a laser cutter posed a risk of damage; therefore, MATLAB was used to accurately partition the images while minimizing the risk of damage, resulting in Fabric 5. This approach reduced material and labor costs, allowed for quick adjustments to create CNN-compatible data, and offered industrial advantages in terms of resource efficiency and quality control. Through this method, a total of 550 image data points for CNN training were obtained (Fabric 5) (Table 1).

Table 1. Fabric classification based on image processing methods.

Fabric Name	Fabric Processing Method	Quantity
Fabric	Spandex 95% + Cotton 5% Fabric, 300 cm × 300 cm	1
Fabric 1	Fabric cut into 10 cm × 10 cm	22
Fabric 2	Fabric treated with dip coating	22
Fabric 3	Digitized images of scanned fabric	22
Fabric 4	Digital images processed with grayscale preprocessing	22
Fabric 5 (Final image data)	Images divided into 25 segments using MATLAB R2023	550

Finally, for each region corresponding to Fabric 5, resistance was measured 20 times using a multimeter (3244-60 (HIOKI E.E. CORPORATION, Nagano, Japan)), and the average value was used as a label to create a precisely labeled image dataset. This dataset played a crucial role in the effective training of the CNN model and in the evaluation of conductivity and CV.

2.3. CNN Architecture and Training

In this study, a convolutional neural network (CNN) model was used to evaluate the electrical uniformity of conductive fabrics. A CNN is a deep learning model for image recognition and processing, which effectively identifies patterns and features in two-dimensional data, making it useful for various computer vision tasks such as image classification and object detection. We utilized MATLAB's Neural Network Toolbox, a widely used commercial numerical analysis and programming environment in engineering and science, to directly define and build a custom neural network architecture for evaluating the electrical performance and CV of conductive fabrics. The CNN algorithm proposed in this paper learns the relationship between resistance and grayscale values to predict resistance and derives the CV by calculating the mean and standard deviation of the predicted resistance values (Figure 4). The CNN model takes single-channel (grayscale) images of size 288×288 as input and automatically extracts features. The first convolutional layer employs 64 filters of size 32×32 with 'same' padding to extract features, applying batch normalization and the Rectified Linear Unit (ReLU) activation function to enhance learning stability and non-linearity. This is followed by a 2×2 max pooling layer to reduce the spatial dimensions. The second and third convolutional layers use 64 filters of sizes 16×16 and 2×2, respectively, to extract more detailed features, repeating the same padding, batch normalization, ReLU, and max pooling processes. The extracted feature maps are flattened into a one-dimensional vector and input into a fully connected layer, where every neuron is connected to all neurons in the previous layer. Finally, the output layer uses a regression activation function to predict the electrical resistance values.

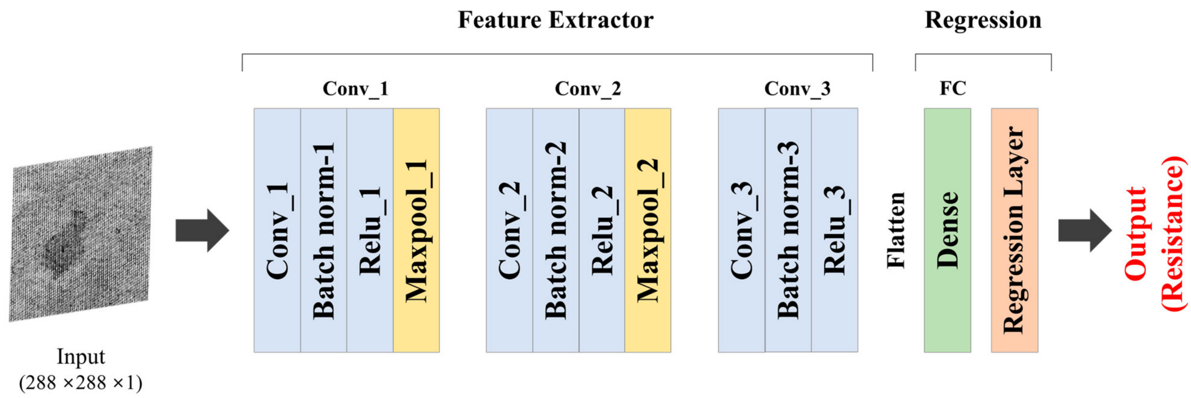


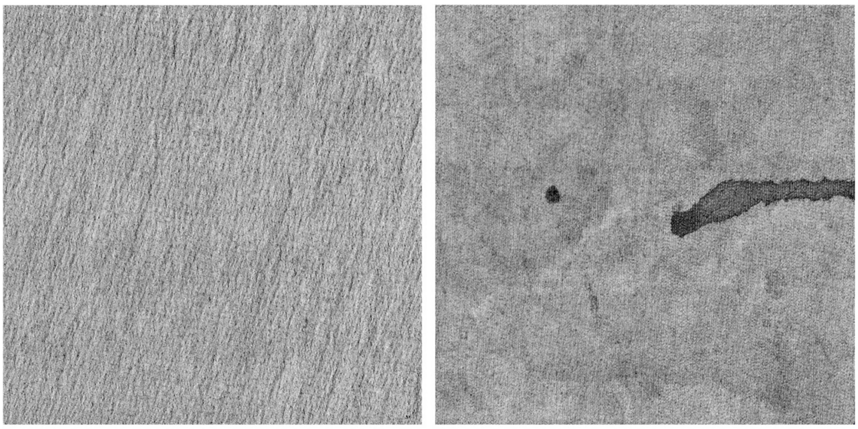
Figure 4. CNN architecture.

2.4. CV Calculation and Evaluation Method

The primary objective of this study is to evaluate the electrical uniformity of conductive fabrics. The average resistance value of conductive fabrics alone is not sufficient to ensure their performance and reliability. Electrical uniformity is crucial because sensors or wearable devices based on conductive fabrics can operate stably only when the fabrics exhibit consistent electrical properties. Therefore, this study utilized the CV to more accurately assess the electrical uniformity of conductive fabrics. CV, which is the standard deviation divided by the mean, was used as a key metric to quantitatively evaluate how consistent the resistance values of the fabric were.

$$\text{CV}\ (\%) = \frac{\text{Standard deviation}}{\text{Mean}} \times 100$$

Figure 5 shows images of two conductive fabrics with similar average resistance values but differing CV. Table 2 shows the results of calculating the average resistance values for each fabric by dividing them into 25 regions and measuring resistance 20 times per region. The table presents both the overall average resistance and the standard deviation based on the resistance values from these 25 regions. Although the average resistance values for both fabrics are approximately 1.75 kΩ, there is a notable difference in the standard deviation of the resistance values. Figure 5a illustrates a fabric that has been uniformly dip-coated, resulting in a low standard deviation and, consequently, a low CV. In contrast, Figure 5b shows a fabric with a higher standard deviation, leading to a higher CV. As such, there are limitations to evaluating the electrical properties of conductive fabrics solely based on the average resistance value. To accurately evaluate the performance of conductive fabrics, it is necessary to analyze the spatial uniformity of the electrical properties, considering both the distribution and variability of resistance within the fabric. The uniformity is a critical factor in ensuring the consistency and reliability of its electrical properties, as the resistance value in specific areas can significantly influence the overall average. Therefore, for accurate evaluation of conductive fabrics, it is essential to analyze both the distribution and variability of resistance rather than relying solely on the average resistance value. Finally, we conducted the CV evaluation using the method shown in Figure 6.



(a) (b)

Figure 5. Comparison of two fabrics with similar mean electrical resistance but different standard deviations: (**a**) fabric with low resistance standard deviation and (**b**) fabric with high resistance standard deviation.

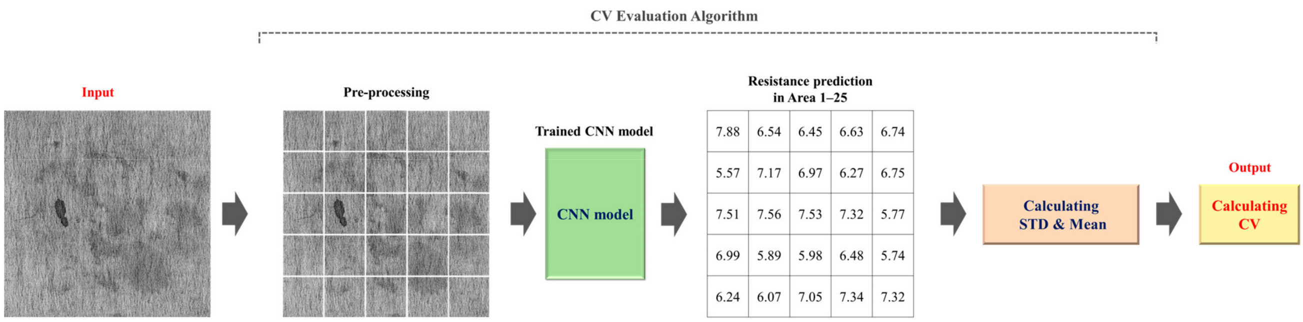


Figure 6. Method for evaluating coefficient of variation (CV).

We trained the CNN model using the Fabric 5 data, which were divided into 25 smaller images for each fabric. Afterward, to verify the prediction performance of the trained model, we prepared the original images. The CV evaluation algorithm automatically split the original image into 25 small pieces of 5 × 5 size, and each sub-image was input into the trained CNN model to predict the electrical resistance value. Based on the 25 predicted resistance values, the mean and standard deviation were calculated, and the final CV value was derived. Using this method, we evaluated the electrical uniformity of the conductive fabrics, and the CV evaluation allowed us to quantitatively assess the uniformity and quality of the fabrics.

Table 2. Comparison of resistance, mean resistance, standard deviation (SD), and coefficient of variation (CV) between Fabrics 5-(a) and 5-(b).

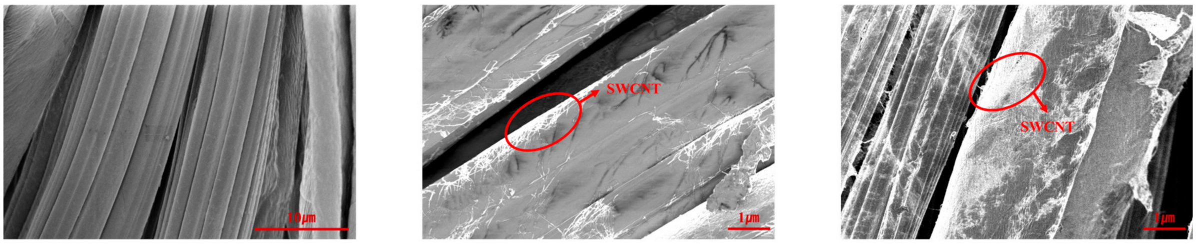
		(a)	(b)
Resistance (kΩ)	1	1.752	2.093
	2	1.457	1.843
	3	1.782	2.069
	4	1.565	2.132
	5	2.039	2.135
	6	1.769	1.846
	7	1.573	1.936
	8	1.875	2.006
	9	1.765	1.749
	10	1.962	1.702
	11	1.668	1.555
	12	1.531	0.978
	13	1.948	2.438
	14	1.913	0.361
	15	1.824	0.562
	16	1.836	1.854
	17	1.664	2.064
	18	1.779	1.91
	19	1.819	2.077
	20	1.944	1.767
	21	1.49	2.098
	22	1.517	1.799
	23	1.755	1.669
	24	1.651	2.113
	25	1.944	1.751
Mean (kΩ)		1.753	1.780
SD		0.164	0.481
CV(%)		9.36	27.02

3. Results

3.1. Characterization of Conductive Fabric

In this study, scanning electron microscopy (SEM) analysis and resistance measurements were performed to evaluate the conductivity characteristics of cotton–spandex blend fabrics treated with SWCNT dip-coating. SEM images visually reveal the distribution of conductive particles within the fabric, and the analysis includes the effects of different dip-coating cycles on particle distribution and resistance.

Figure 7 provides SEM (the ZEISS Gemini SEM 300, Oberkochen, Germany) images, where (a) shows the image of the untreated cotton–spandex fabric, and (b) and (c) depict fabrics treated with 2 and 6 dip-coating cycles, respectively. In Figure 7b,c, it can be observed that conductive particles are distributed within the fabric after dip-coating. The images also indicate that as the number of dip-coating cycles increases, the particles become more densely distributed on the fiber surface and within the fabric. This suggests that with an increasing number of dip-coating cycles, the number of conductive particles increases, forming electrical pathways as these particles connect. Table 3 shows the resistance measurement results for the fabrics depicted in Figure 7b,c. The data indicate a significant reduction in electrical resistance with an increasing number of dip-coating cycles. The average resistance value decreased from 4.44 Ω for the fabric with two dip-coating cycles to 1.75 Ω for the fabric with six dip-coating cycles. This reduction suggests that with more dip-coating cycles, the distribution of conductive particles becomes more uniform, and the electrical connectivity improves. The SEM images and resistance measurement results clearly demonstrate the impact of the number of dip-coating cycles on the electrical properties of the conductive fabrics, proving that dip-coating is an effective method for controlling electrical characteristics.



(a) (b) (c)

Figure 7. SEM images: (**a**) no dip-coating, (**b**) dip-coating 2 cycles, and (**c**) dip-coating 6 cycles.

Table 3. Fabric resistance of 7-(a), (b), and (c).

	Fabric		
	No Dip-Coating (7-(a))	**Dip-Coating 2 Cycles (7-(b))**	**Dip-Coating 6 Cycles (7-(c))**
Resistance (kΩ)	∞	4.44	1.75

3.2. Dataset Analysis and Image Processing Outcome

In this study, accurate data collection and preprocessing are key factors in evaluating the electrical performance and uniformity of conductive fabrics using CNNs. Proper data collection and preprocessing play a critical role in ensuring the performance and accuracy of the model. To efficiently perform CNN training, we scanned a total of 22 Fabric 2 samples to obtain Fabric 3 and then applied grayscale preprocessing to create Fabric 4. Subsequently, using MATLAB, we divided Fabric 4 into 25 regions of 288 × 288 pixels to create Fabric 5, which will be used for CNN model training. Figure 8 visually explains how Fabric 4 is divided into Fabric 5. The final Fabric 5 dataset provides critical data for the precise analysis of the electrical properties of conductive textiles.

After the image collection stage is completed, the process of obtaining accurate labels begins. In this study, the resistance values of each Fabric 5 region were used as labels to analyze electrical properties and uniformity. Using a digital multimeter (HIOKI 3244-60, HIOKI Korea, Seoul, Republic of Korea), the resistance of each region was measured, and the obtained resistance values were applied as labels for the corresponding regions. To ensure precise labeling, resistance was measured 20 times for each region, and the average of these measurements was used as the final label.

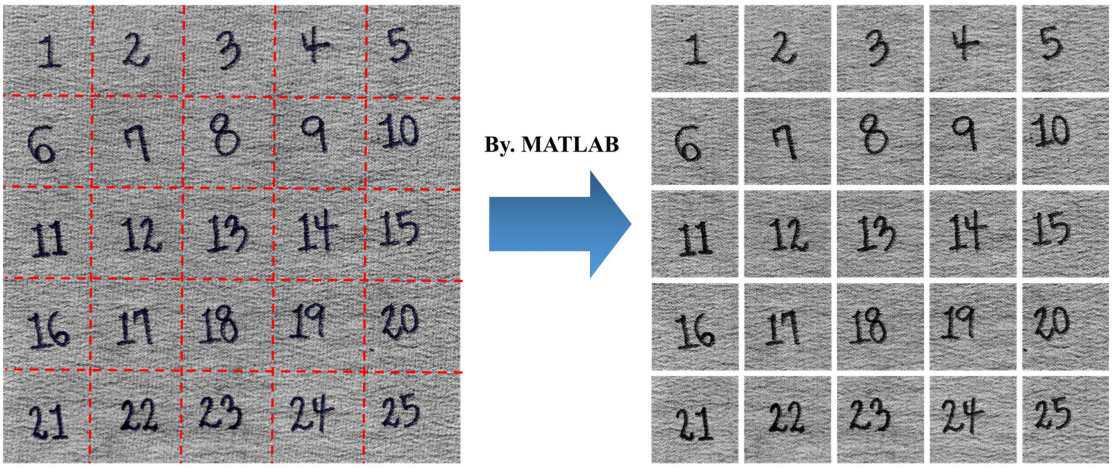


Figure 8. Method for obtaining Fabric 5.

3.3. CNN Model Performance

The experiments in this study were conducted using MATLAB R2023 software on a system based on the Z790 AORUS ELITE motherboard, equipped with a 13th Gen Intel® Core™ i9-13900K processor (3.00 GHz), 32 GB of memory, and an NVIDIA GeForce RTX 4090 graphics card (driver version 536.40). The proposed CNN model was designed to predict resistance through the relationship between resistance and contrast in conductive fabrics, using surface images of the conductive fabrics as input. A total of 85% of the dataset was randomly split for training the CNN, while the remaining 15% was used as test data. After multiple trials and validations, we optimized the model by setting the MiniBatchSize to 16, MaxEpochs to 200, and InitialLearnRate to 0.001. During the training process, we observed the changes in training loss and validation loss. We found that starting with an initial learning rate of 0.001 and reducing the learning rate by a factor of 0.6 at each learning rate decay period was effective in improving both the stability and convergence speed of the training. Notably, a sharp decrease in loss was observed during the first epoch, followed by a gradual reduction in loss as training progressed (Figures 9 and 10). To evaluate the performance of the proposed CNN model, the predicted electrical resistance values were compared with the actual values using a test dataset, and the coefficient of determination (R^2) was calculated (Figure 11). The R^2 value obtained in this study is 0.9422, indicating that the proposed model demonstrates very high accuracy in predicting electrical resistance and generates results closely aligned with actual data. This result suggests that the proposed CNN model can be a reliable tool for predicting the electrical resistance of conductive fabrics.

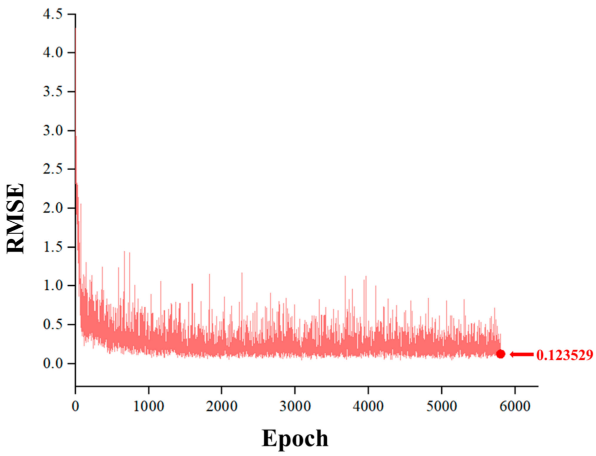


Figure 9. CNN training process—RMSE.

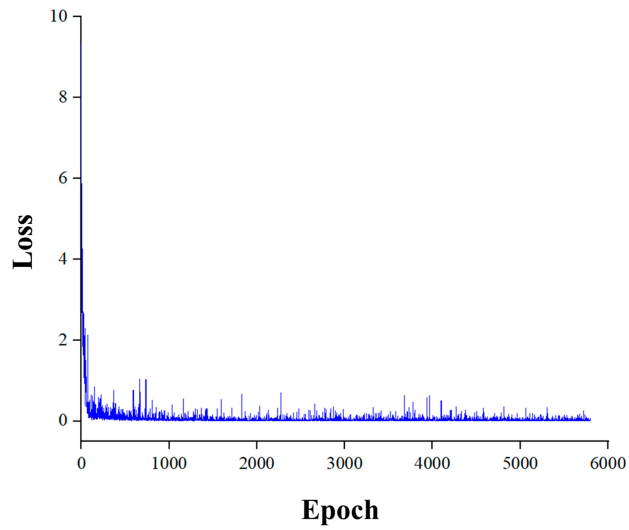


Figure 10. CNN training process—loss.

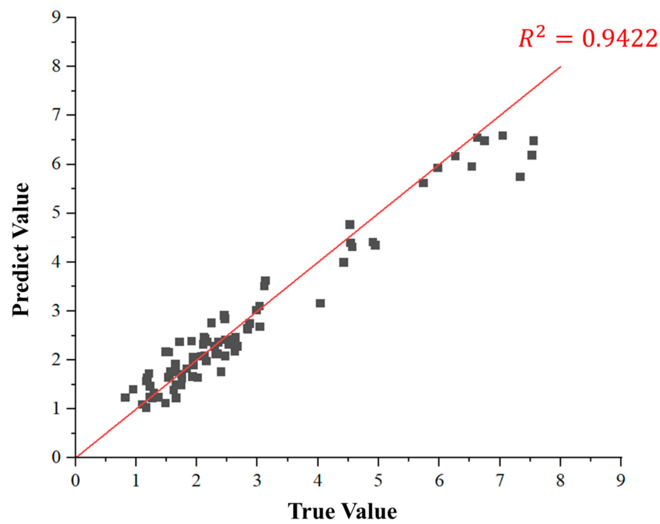


Figure 11. CNN test results—comparison between true and predicted values.

3.4. CV Analysis and Model Accuracy

In this study, the proposed CNN-based image analysis method was used to evaluate the electrical properties and coefficient of variation (CV) of SWCNT dip-coated conductive fabrics. The experimental results showed that the CV measurement method used to assess the uniformity of the conductive fabrics demonstrated high accuracy. We evaluated the CV for two types of fabrics: uniformly dip-coated fabrics (uniform fabrics) and non-uniformly dip-coated fabrics (non-uniform fabrics). Each fabric was divided into 25 small regions, and the resistance was measured 10 times in each region to calculate the average resistance value. Using this method, we calculated the overall average resistance and standard deviation of the conductive fabrics and, based on these values, determined the CV. For the uniform fabric, the actual average resistance was 2.64 kΩ, with a standard deviation of 0.18, resulting in a calculated CV value of 6.84%. Using the CNN model, the predicted average resistance was 2.61 kΩ, with a standard deviation of 0.18. The CV value calculated through the CNN model was 6.90%, demonstrating a high accuracy of 99.1792% in the predicted CV value. This indicates that the proposed CNN model can accurately assess the CV value of uniformly coated fabrics. For the non-uniform fabric, the actual average resistance was 1.78 kΩ, with a standard deviation of 0.48, resulting in a CV value of 27.04%. The CNN model predicted an average resistance of 1.85 kΩ, with a standard deviation of

0.48, which was similarly high compared to the actual values. The CV value calculated from the predicted data was 26.20%, showing an accuracy of 96.8877%. This indicates that the proposed CNN model can also evaluate the CV value of non-uniformly coated fabrics with high accuracy (Figure 12). These results highlight that the proposed CNN model is useful and suitable for assessing the uniformity of fabrics treated with conductive solution dip-coating. Specifically, the high accuracy in predicting CV values suggests that the model can effectively analyze and evaluate the uniformity and variability of the fabrics. To further assess the reliability of the model's predictive performance, the differences between the CNN model's predicted CV values and the actual CV values for all fabric samples were analyzed, and a *p*-value was calculated. The *p*-value serves as an indicator to determine whether there is a statistically significant difference between the predicted and actual values. In this study, the *p*-value was found to be 0.96044. This value is much higher than commonly used significance levels, indicating that there is no statistically significant difference between the CV values predicted by the CNN model and the actual CV values. In other words, this demonstrates that the model's predictions are highly similar to the actual measurements, supporting the high predictive accuracy of the proposed CNN model. Such *p*-value analysis confirms that the CNN-based image analysis method can reliably evaluate the CV values of both uniformly and non-uniformly coated fabrics. It demonstrates that the model proposed in this study is effective for assessing the electrical properties and uniformity of conductive fabrics overall).

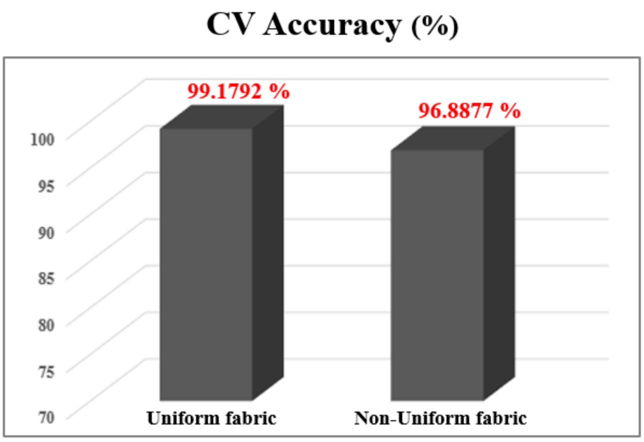


Figure 12. CV accuracy (%).

4. Discussion

In this study, a conductive fabric was produced by applying SWCNT dip-coating to spandex fabric containing cotton, and its electrical uniformity was quantitatively evaluated using a CNN-based image analysis. Several key findings were observed. First, it was found that the electrical resistance of the fabric significantly decreased as the number of dip-coating applications increased. The fabric dip-coated twice showed an average resistance of 3 Ω, whereas the fabric with six coating layers had a reduced resistance of 1 Ω. This reduction in resistance can be attributed to the more uniform distribution of SWCNT particles and the improved electrical connectivity resulting from an increased number of coating layers. SEM image analysis confirmed that as the number of dip-coating layers increased, the conductive particles were more densely distributed within the fabric, reinforcing the conductive pathways. In the data analysis using the CNN model, a preprocessing step converting the images to grayscale was applied, reducing noise and improving computational efficiency. Through hyperparameter optimization, the model demonstrated excellent performance in terms of mean absolute error (MAE) and mean squared error (MSE), validating its predictive capability for the electrical properties of the conductive fabric. Additionally, when assessing the uniformity of the conductive fabric by measuring the coefficient of variation (CV), the model achieved a very high prediction accuracy of 99.1792% for uniformly coated fabrics and 96.9977% for non-uniformly coated fabrics. To comprehensively evaluate the model's predictive performance, the differences between the CNN model's predicted CV values and the actual CV values for all fabric samples were analyzed, and a *p*-value was calculated. The *p*-value was found to be 0.96044, which is significantly higher than the commonly used significance level (e.g., 0.05). This indicates that there is no statistically significant difference between the predicted and actual CV values of the CNN model. These results support the high predictive accuracy and reliability of the proposed model, as its predictions are highly similar to the actual measurements. This study primarily focused on samples with uniform or slightly non-uniform characteristics, so additional research is necessary to evaluate the model's performance on extremely non-uniform samples. Such studies will help assess and enhance the model's robustness. Future research should include various conductive materials and manufacturing conditions to validate the model's performance and explore its applicability under more complex conditions. This could improve the generalizability of the proposed CNN model and contribute to quality assurance and process automation for conductive materials.

5. Conclusions

This study quantitatively evaluated the electrical properties and uniformity of cotton–spandex blended fabric produced through SWCNT dip-coating using a CNN-based image analysis. SEM analysis and resistance measurements confirmed that as the number of dip-coating layers increased, the uniform distribution of conductive particles and electrical connectivity improved, resulting in decreased electrical resistance. The proposed CNN model was optimized through grayscale preprocessing and hyperparameter tuning, achieving high predictive accuracy with an R-squared (R^2) value of 0.9422. In the CV prediction, the model demonstrated a high prediction accuracy of 99.18% for uniformly coated fabrics and 96.89% for non-uniformly coated fabrics, validating its effectiveness. Additionally, a *p*-value of 0.96044 was obtained for all fabric samples, indicating no statistically significant difference between the predicted and actual CV values, thereby supporting the reliability of the model's predictions. This study suggests that CNN-based image analysis can serve as a powerful tool for quality control and process optimization of conductive fabrics. The proposed approach is expected to be applicable to various conductive materials and manufacturing processes, showing potential for contributing to quality assurance and process automation in industrial settings. Future research should focus on enhancing the robustness of the model and evaluating its performance on extremely non-uniform samples to expand its applicability under diverse conditions. Such studies would improve the generalizability of the CNN model and contribute to quality assurance and production process automation for conductive materials.

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Appendix A

Table A1. Nomenclature.

Term	Definition
SWCNT (Single Wall Carbon Nanotube)	A type of carbon nanotube consisting of a single cylindrical layer of carbon atoms. It is known for its high electrical conductivity, flexibility, and lightweight properties.
CV (Coefficient of Variation)	A measure of relative variability. It is calculated as the ratio of the standard deviation to the mean, expressed as a percentage.
CNN (Convolutional Neural Network)	A type of deep learning model commonly used for image recognition and processing. It is particularly effective for detecting and learning patterns in two-dimensional data.
SEM (Scanning Electron Microscopy)	A technique for high-resolution imaging to analyze the surface structure of materials.
Grayscale Preprocessing	The process of converting color images to grayscale to reduce data complexity and enhance model training efficiency.

References

1. Coyle, S.; Diamond, D. 10-Medical applications of smart textiles. In *Advances in Smart Medical Textiles*; van Langenhove, L., Ed.; Woodhead Publishing Series in Textiles; Woodhead Publishing: Oxford, UK, 2016; pp. 215–237, ISBN 978-1-78242-379-9.
2. Smart Textiles for Personalized Healthcare | Nature Electronics. Available online: https://www.nature.com/articles/s41928-022-00723-z (accessed on 19 August 2024).
3. Meena, J.S.; Choi, S.B.; Jung, S.-B.; Kim, J.-W. Electronic textiles: New age of wearable technology for healthcare and fitness solutions. *Mater. Today Bio* **2023**, *19*, 100565. [CrossRef] [PubMed]
4. Cho, S.; Chang, T.; Yu, T.; Lee, C.H. Free Full-Text | Smart Electronic Textiles for Wearable Sensing and Display. *Biosensors* **2022**, *12*, 222.
5. Soroudi, A.; Hernández, N.; Wipenmyr, J.; Nierstrasz, V. Surface modification of textile electrodes to improve electrocardiography signals in wearable smart garment. *J. Mater. Sci. Mater. Electron.* **2019**, *30*, 16666–16675. [CrossRef]
6. A Piezoelectric Smart Textile for Energy Harvesting and Wearable Self-Powered Sensors. *Energies* **2022**, *15*, 5541. [CrossRef]
7. Gyo Jeong, E.; Jeon, Y.; Ho Cho, S.; Cheol Choi, K. Textile-based washable polymer solar cells for optoelectronic modules: Toward self-powered smart clothing. *Energy Environ. Sci.* **2019**, *12*, 1878–1889. [CrossRef]
8. Zhao, W.; Zheng, Y.; Qian, J.; Zhaofa, Z.; Jin, Z.; Qiu, H.; Zhu, C.; Hong, X. AgNWs/MXene derived multifunctional knitted fabric capable of high electrothermal conversion efficiency, large strain and temperature sensing, and EMI shielding. *J. Alloys Compd.* **2022**, *923*, 166471. [CrossRef]
9. Li, S.-H.; Li, J. Smart patch wearable antenna on Jeans textile for body wireless communication. In Proceedings of the 2018 12th International Symposium on Antennas, Propagation and EM Theory (ISAPE), Hangzhou, China, 3–6 December 2018; pp. 1–4.
10. Castano, L.M.; Flatau, A.B. Smart fabric sensors and e-textile technologies: A review. *Smart Mater. Struct.* **2014**, *23*, 053001. [CrossRef]
11. Materials, Preparation Strategies, and Wearable Sensor Applications of Conductive Fibers: A Review. *Sensors* **2022**, *22*, 3028. [CrossRef]
12. Overview of the Influence of Silver, Gold, and Titanium Nanoparticles on the Physical Properties of PEDOT:PSS-Coated Cotton Fabrics. *Nanomaterials* **2022**, *12*, 1609. [CrossRef]
13. PEDOT:PSS-Based Conductive Textiles and Their Applications. *Sensors* **2020**, *20*, 1881. [CrossRef]
14. Conductive Silver Inks and Their Applications in Printed and Flexible Electronics—RSC Advances (RSC Publishing). Available online: https://pubs.rsc.org/en/content/articlehtml/2015/ra/c5ra12013f (accessed on 19 August 2024).
15. Silver Nanoparticle Conductive Inks: Synthesis, Characterization, and Fabrication of Inkjet-Printed Flexible Electrodes | Scientific Reports. Available online: https://www.nature.com/articles/s41598-020-65698-3 (accessed on 19 August 2024).
16. Meirowitz, R.E. 8-Coating processes and techniques for smart textiles. In *Active Coatings for Smart Textiles*; Hu, J., Ed.; Woodhead Publishing Series in Textiles; Woodhead Publishing: Oxford, UK, 2016; pp. 159–177, ISBN 978-0-08-100263-6.
17. Grancarić, A.M.; Jerković, I.; Koncar, V.; Cochrane, C.; Kelly, F.M.; Soulat, D.; Legrand, X. Conductive polymers for smart textile applications. *J. Ind. Text.* **2018**, *48*, 612–642. [CrossRef]
18. Thangakameshwaran, N.; Santhoskumar, A.U. Cotton Fabric Dipped in Carbon Nano Tube Ink for Smart Textile Applications. *Int. J. Polym. Mater. Polym. Biomater.* **2014**, *63*, 557–562. [CrossRef]

19. Alhashmi Alamer, F.; Almalki, G.A. Fabrication of Conductive Fabrics Based on SWCNTs, MWCNTs and Graphene and Their Applications: A Review. *Polymers* **2022**, *14*, 5376. [CrossRef] [PubMed]
20. Wang, G.; Long, S.; Yu, Z.; Zhang, M.; Ye, T.; Li, Y.; Xu, D.; Lv, H.; Liu, Q.; Wang, M.; et al. Improving resistance uniformity and endurance of resistive switching memory by accurately controlling the stress time of pulse program operation. *Appl. Phys. Lett.* **2015**, *106*, 092103. [CrossRef]
21. Lee, W.; Park, J.; Kim, S.; Woo, J.; Shin, J.; Lee, D.; Cha, E.; Hwang, H. Improved switching uniformity in resistive random access memory containing metal-doped electrolyte due to thermally agglomerated metallic filaments. *Appl. Phys. Lett.* **2012**, *100*, 142106. [CrossRef]
22. Xu, N.; Fang, L.; Chi, Y.; Zhang, C.; Tang, Z. Resistance uniformity of TiO_2 memristor with different thin film thickness. In Proceedings of the 14th IEEE International Conference on Nanotechnology, Toronto, ON, USA, 18–21 August 2014; pp. 727–731.
23. Doherty, E.M.; De, S.; Lyons, P.E.; Shmeliov, A.; Nirmalraj, P.N.; Scardaci, V.; Joimel, J.; Blau, W.J.; Boland, J.J.; Coleman, J.N. The spatial uniformity and electromechanical stability of transparent, conductive films of single walled nanotubes. *Carbon* **2009**, *47*, 2466–2473. [CrossRef]
24. Ghalamboran, M.; Nazeri, M.; Grau, G. Pattern-dependent resistivity variations in inkjet-printed conductors due to non-uniform ink drying. *Flex. Print. Electron.* **2024**, *9*, 015011. [CrossRef]
25. Jayathilaka, W.A.D.M.; Chinnappan, A.; Ramakrishna, S. A review of properties influencing the conductivity of CNT/Cu composites and their applications in wearable/flexible electronics. *J. Mater. Chem. C* **2017**, *5*, 9209–9237. [CrossRef]
26. Flexible Electronics Toward Wearable Sensing | Accounts of Chemical Research. Available online: https://pubs.acs.org/doi/full/10.1021/acs.accounts.8b00500 (accessed on 4 November 2024).
27. Mapping the Progress in Flexible Electrodes for Wearable Electronic Textiles: Materials, Durability, and Applications—Liman—2022—Advanced Electronic Materials—Wiley Online Library. Available online: https://onlinelibrary.wiley.com/doi/full/10.1002/aelm.202100578?_utm_campaign=mention57529&_utm_content=lnk241316896300&_utm_medium=inline&_utm_source=xakep (accessed on 4 November 2024).
28. Lai, G.; Chang, W.-C.; Yang, Y.; Liu, H. Modeling Long- and Short-Term Temporal Patterns with Deep Neural Networks. In Proceedings of the 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, Ann Arbor, MI, USA, 8–12 July 2018; Association for Computing Machinery: New York, NY, USA, 2018; pp. 95–104.
29. Traore, B.B.; Kamsu-Foguem, B.; Tangara, F. Deep convolution neural network for image recognition. *Ecol. Inform.* **2018**, *48*, 257–268. [CrossRef]
30. Li, Z.; Liu, F.; Yang, W.; Peng, S.; Zhou, J. A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects. *IEEE Trans. Neural Netw. Learn. Syst.* **2022**, *33*, 6999–7019. [CrossRef]
31. Convolutional Neural Network: A Review of Models, Methodologies and Applications to Object Detection | Progress in Artificial Intelligence. Available online: https://link.springer.com/article/10.1007/s13748-019-00203-0 (accessed on 19 August 2024).
32. Zheng, X.; Zheng, S.; Kong, Y.; Chen, J. Recent advances in surface defect inspection of industrial products using deep learning techniques. *Int. J. Adv. Manuf. Technol.* **2021**, *113*, 35–58. [CrossRef]
33. Deep Learning-Based Fabric Defect Detection: A Review—Yavuz Kahraman, Alptekin Durmuşoğlu. 2023. Available online: https://journals.sagepub.com/doi/full/10.1177/00405175221130773 (accessed on 20 August 2024).
34. Full Article: Automatic Defect Detection for Fabric Printing Using a Deep Convolutional Neural Network. Available online: https://www.tandfonline.com/doi/full/10.1080/17543266.2021.1925355 (accessed on 4 November 2024).
35. Jing, J.-F.; Ma, H.; Zhang, H.-H. Automatic fabric defect detection using a deep convolutional neural network. *Color. Technol.* **2019**, *135*, 213–223. [CrossRef]
36. Ouyang, W.; Xu, B.; Hou, J.; Yuan, X. Fabric Defect Detection Using Activation Layer Embedded Convolutional Neural Network. *IEEE Access* **2019**, *7*, 70130–70140. [CrossRef]
37. UmaRani, V.; Srimathi, S. Automatic Fabric Defect Detection using Deep CNN-AlexNet Models. In Proceedings of the 2024 2nd International Conference on Device Intelligence, Computing and Communication Technologies (DICCT), Dehradun, India, 15–16 March 2024; pp. 1–6.
38. Sabeenian, R.S.; Paul, E.; Prakash, C. Fabric defect detection and classification using modified VGG network. *J. Text. Inst.* **2023**, *114*, 1032–1040. [CrossRef]
39. Fabric Defect Detection in Real World Manufacturing Using Deep Learning. *Information* **2024**, *15*, 476. [CrossRef]