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REGULAR ARTICLE

Quality Control Model for Electrospun Nanofibers through Image Analysis

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Electrospinning Nanofibers are extensively used in progressive fields such as biomedical engineering for tissue scaffolds, filtration for air and water, and energy storage, among others, due to their high surface area-to-volume ratio. Nevertheless, one of the most frequent problems in this area is the inability to exercise strict control over the quality of a particular production batch, which occasionally results in a stark fluctuation in performance. This study addresses this issue by proposing the Efficient Slime Mould Algorithm fine-tuned Adaptive Deep Residual Network (ESMA-ADRN), designed to improve the quality valuation of electrospun nanofibers over advanced image examination. The dataset employed in this research includes images of electrospun nanofiber images, which are subjected to preprocessing through a median filter as a denoising technique. The process of feature extraction has been carried out using Principle Component Analysis (PCA) to determine the most useful feature space for classification. The results of the proposed ESMA-ADRN models show notable numeric values when compared to other models that lead to high achievements, such as accuracy maximum of 94.30 %, precision 96.58 %, sensitivity 93.04 %, specificity 93.72 %, and F-score of 94.77%.Future work should continue to compile more scenarios for the trained model to cover more possibilities and the adjustment and refining of the model parameter for better performance in many manufacturing situations.

Keywords: Electrospun nanofibers, Quality control, Image analysis, Deep neural network, ESMA-ADRN, PCA.

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1. INTRODUCTION

Electrospinning is a universal and frequently used method to obtain nanofibers and nanoscaled fiber structures with ultra-large surface area, small diameter high mechanical strength, and other related properties. These attributes qualify electrospun nanofibers for applications, such as biomedical devices, filtration materials, tissue template engineering scaffolds, and sensors among others. However, the quality and uniformity of nanofibers spun through the electrospinning process are highly essential to their performance in these uses [1]. Thus, the creation of reliable methods for quality control (QC) is crucial to control and stabilize the required properties of electrospun nanofibers during their fabrication [2]. The conventional approaches in QC are normally based on a physical and mechanical examination that is normally lengthy and does not effectively offer details of the topography of the nanofibers, as seen in the present study. However, these methods are not enough to determine small differences in fiber diameter, orientation, or surface roughness that can affect the performance of the nanofiber material [3]. Recent developments in high-definition image analysis techniques have been recognized as potential approaches to improve the quality of electrospun nanofibers. Through the use of digital imaging and highly advanced statistical calculations, researchers can accurately deduce desirable features of nanofibers with a higher degree of precision than before [4]. Image analysis is used in the quantification of the nanofiber structure, such as the diameter, length, orientation, and distribution of the nanofibers. Through scanning electron microscopy (SEM) or optical microscopy and image analyzing software, one can successfully image and build the profiles of the nanofiber networks [5]. Such profiles can demonstrate irregularities in the body of the fiber that are discernible under conventional testing techniques. Second, it is possible to combine machine learning and artificial intelligence to establish an automated system to monitor

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the image of different products in real time to recognize defects or inconsistencies [6]. The integration of image analysis methods into the current QC paradigm for electrospun nanofibers can improve the precision and uniformity of the nanofiber fabrication process [7]. Incorporating image processing technologies coupled with quality indices, problems affecting fiber quality can be anticipated and solved by the manufacturers hence enhancing the quality of subsequent finished products [8]. Furthermore, proper QC models based on images which can provide insight into influencing factors that affect nanofiber fabrication [9]. It done by observing and comparing the cross-sectional morphology of nanofibers processed under different conditions comprising voltage, flow rate, and solution viscosity [10]. Such knowledge can result in improved electrospinning techniques that would allow for the fabrication of nanofibers with desired characteristics for various applications. In general, incorporating image analysis in the QC of electrospun nanofibers is a major improvement in the area of nanofiber studies and production [11-12]. The objective of this research is to categorize the quality of electrospun nanofibers using cloning that incorporates the Efficient Slime Mould Algorithm fine-tuned Adaptive Deep Residual Network (ESMA-ADRN). With better network tuning and optimization with enhanced search algorithms, the study aims at bettering the accuracy of the classification model, thereby improving the QC process in the fabrication of nanofibers.

2. RELATED WORKS

Nanotechnology is widely studied because nanomaterials possess enhanced chemical, physical, and environmental properties. Electrospinning was a complex technique used to fabricate ultrafine microfibers and membranes with different properties. These fibers could be used for various functions, including tissue healing, drug delivery, and enzyme confinement. A study [13] investigated the impacts of process variables on nanofiber properties and discovered that the ideal focus, molecular mass, and conductance result in identical, smooth, and thinner nanofibers. Environmental circumstances have an impact on the dimension and caliber of nanofibers. Electrospinning was a process for generating polymer non-woven frameworks out of nano and microfibers that proved useful in biological sectors.

3. MATERIALS AND METHODS

The complete procedure for initiating a QC model of electrospun nanofibers is described. These are the dataset and some of the preprocessing steps followed by applying a median filter that aims at removing noise while time maintaining edges and feature extraction through PCA. Further, the proposed method ESMA-ADRN model with advanced optimization to increase the model precision and perform the high-quality analysis of the nanofiber images.

3.1 Dataset

The primary dataset comprises SEM images specifically collected to assess and analyze the quality of electrospun nanofibers. This dataset is crucial for developing a robust QC model that leverages image analysis techniques to evaluate nanofiber characteristics effectively. The dataset includes 200 SEM images showcasing a diverse range of electrospun nanofibers, providing a comprehensive overview of various quality parameters such as fiber diameter, uniformity, and morphological features (table 1). The images vary in size, ranging from 512 x 512 pixels to 2048 x 2048 pixels, allowing for high-resolution analysis and detailed examination of fiber structures. Each image is annotated with key quality indicators, including the measured fiber diameter (ranging from 100 nm to 1 μm), alignment characteristics, and the presence of defects like beads or irregularities. This structured dataset not only facilitates the training and validation of the QC model but also enhances the correctness of the image analysis.

Table 1 – Dataset Description

Image ID	**Image Size (pixels)**	**Fiber Diameter (nm)**	**Quality Indicators**
1	512 x 512	120	Uniform, No Defects
2	1024 x 1024	150	Slightly Irregular, Beads
3	2048 x 2048	200	Uniform, No Defects
4	1024 x 768	80	Irregular, Beads Present
5	1536 x 1536	250	Uniform, No Defects
6	800 x 800	100	Slightly Irregular
7	1280 x 720	300	Uniform, No Defects
8	640 x 480	180	Irregular, Beads Present
...	...	...	...
200	2048 x 1536	150	Uniform, No Defects

3.2 Preprocessing using Median Filter

The median filter is a non-linear filtering technique that computes the median of the pixel values in a specified filter mask. Each pixel in the image is processed and replaced by the statistical median of its N×M neighborhood. This method is particularly effective in preserving edge sharpness and high-frequency details, as the median value is derived from surrounding pixels, making it robust to outliers. Unlike linear filters, the median filter does not create unrealistic pixel values, thus minimizing issues, like edge blurring and loss of image detail. The median filter is well-suited for removing salt-and-pepper noise from images. Its effectiveness in noise reduction increases with larger window sizes, allowing for better median estimation from a broader set of neighboring pixels. The equation (1) for the median filter is represented as follows:

$$e(w,z) = \underset{(t,s)\in Twz}{median\{h(t,s)\}} \quad (1)$$

Where Twz denotes the coordinates of the sub-image window of size M × N. By applying the median filter in the QC model, and enhance the clarity and accuracy of the images of electrospun nanofibers, thereby improving the subsequent analysis and optimization processes.

3.3 Feature Extraction Using Principal Component Analysis (PCA)

The fundamental concept of PCA is to linearly transform environmental data collected in the study into a low-dimensional subspace, maximizing the alteration in the dataset. This results in an uncorrelated basis set that illuminates the relationships between various electrospun nanofiber images. In this condition, reflect L clarifications from the image data characterized in n-dimensional space. Compute the mean vector μ of observations using the Eq. (2).

$$\mu = \frac{1}{l}\sum_{j=1}^{l} w_j \quad (2)$$

Use the following Eq. (3) to estimate the matrix of covariance *T* for the provided data:

$$T = \frac{1}{l}\sum_{j=1}^{l}(w_j-\mu)\,(w_j-\mu)^S \quad (3)$$

Ascertain the eigenvalues of the matrix, plus their associated eigenvectors. Use this Eq. (4-6) the essential componentsz from the original variables:

$$z_1 = b_{11}w_1 + b_{12}w_2 + \cdots + b_{1l}w_l \quad (4)$$

$$z_2 = b_{21}w_1 + b_{22}w_2 + \cdots + b_{2l}w_l \quad (5)$$

$$z_x = b_{l1}w_1 + b_{l2}w_2 + \cdots + b_{ll}w_l \quad (6)$$

With these limit points, PCA is guaranteed to sustain the essential features necessary to understand the quality of electrospun nanofiber image analysis.

3.4 Classification of Electrospun Nanofiber Quality through the Efficient Slime Mould Algorithm Fine-tuned Adaptive Deep Residual Network (ESMA-ADRN)

The proposed hybrid ESMA-ADRN model integrates the optimized ESMA with an ADRN to increase the electrospun nanofibers' QC performance. This approach enhances the performance and quality of optimization because it includes more elaborate exploration strategies as well as layer information storage.

3.5 Adaptive Deep Residual Network (ADRN)

They develop the concepts in Deep Residual Network (DRN) to enhance information retention during the transfer between layers, ultimately aiming for higher accuracy. To achieve this to improve the architecture of the DRN and apply to QC in electrospun nanofibers. The network operates as follows: Let the input be denoted as w. The first layer processes this input, fitting the functione (w). Then, combine the outputs by adding them together, resulting in Eq. (7).

$$h(w) = e(w) + w \quad (7)$$

The second layer takes $h(w)$ as input and maps it to $(h(w))$. In the next step, again add the output of the first layer $e(w)$, to the output of the second layer, it yielding Eq. (8).

$$G(w) = g(e(w) + w) + e(w) \quad (8)$$

As seen from the above Eq. (8), it breaks the process of approximating the joint function $G(w)$ into approximating two simpler functions of g. If both of these simple mappings are implemented, the layers will function more efficiently, making them easier to integrate. Therefore, it can lower the chance of error in fitting these two mappings and ultimately lower the total error chance. Fig. 1 represents the architecture of ADRN.

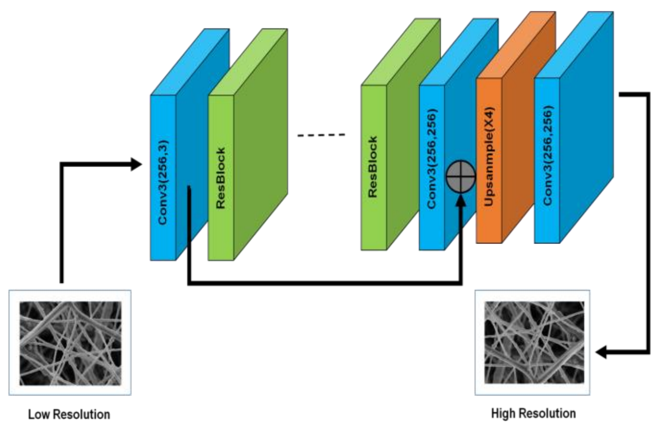

Fig. 1 – ADRN Architecture

3.6 Efficient Slime Mould Algorithm (ESMA)

The standard Slime Mould Algorithm (SMA) is an easy-to-use technique for tackling a variety of optimization issues. However, SMA can get caught in regional optima and show inadequate converging speeds, especially in complicated tasks like multilayer thresholds for segmenting images. To ESMA searches and enhance exploration and exploitation, they suggest an ESMA to improve optimizing efficiency. The enhancements in ESMA focus on two key methods. First, they incorporate Levy flight to augment the exploration ability of SMA. This technique allows for more diverse search patterns, improving the algorithm's capability to explore the solution space more thoroughly and escape local optima.

The Levy Flight can be mathematically represented as follows in Eq. (9):

$$W(\vec{s}+1)=\begin{cases} q_2 \times (VA-KA)-KA, q_1 < y \\ W_a + va \times (X \times W_B - W_A) \times Levy, q_3 < \\ vD \times W_j, q_3 \geq o \end{cases} \quad (9)$$

By integrating these improvements, ESMA aims to achieve more effective optimization process, ultimately enhancing the performance of the DRN for the QC of electrospun nanofibers. Additionally, quasi-opposition-based training is used to increase the ESMA's exploit capabilities and establish an improved ratio of explore and exploit. This approach enhances the algorithm's ability to refine solutions effectively while navigating the solution space. Fig. 2 illustrates the flowchart of the ESMA. These visual representations detail the step-by-step process of ESMA,

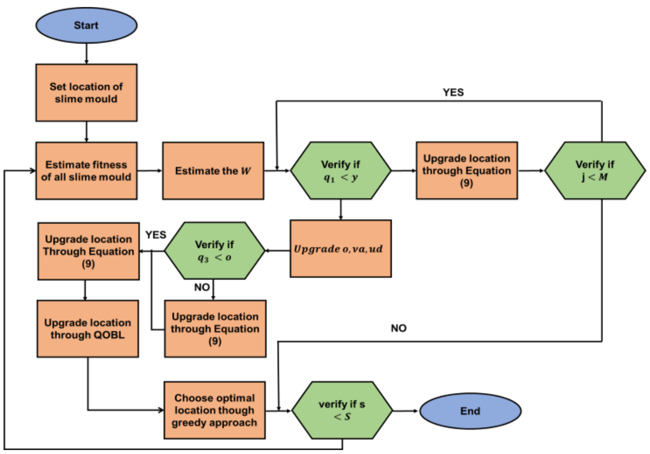

Fig. 2 – ESMA flowchart

4. RESULT AND DISCUSSION

The experiment of a Windows 10×64 operating systems with an Intel(R) Core(TM) i5-3320M CPU at 2.60 GHz with 8.00 GB of RAM provided quite a stable hardware base. The software environment was created using Python 3.11.9 and it helped in the easier construction of the model. The performance of the proposed ESMA-ADRN model to classify quality and defective electrospun nanofibers. These are accuracy, precision, sensitivity, specificity, F-score, and error, such as the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE). Thus, evaluating these metrics between the different model configurations allows to evaluate ESMA-ADRN's effectiveness in enhancing QC by reducing classification errors and increasing predictive effectiveness. These findings provide an extended understanding of the model's ability to identify defects and the potential for enhancing its performance.

4.1 ROC Curve

Fig. 3 curve represents the classification performance of the ESMA-ADRN model in identifying defects or quality issues in electrospun nanofibers based on image data. The x-axis represents the false positive rate, representing the percentage of incorrectly classified negative samples (quality fibers misclassified as defective) relative to all actual negatives. The y-axis represents the true positive rate, or the model's accuracy in correctly identifying defective fibers among all actual defect samples. The curve shows the efficiency of ESMA-ADRN as the classification threshold varies. The dotted line signifies a random classifier with an AUC of 0.5 for baseline comparison. The area under the curve (AUC) for ESMA-ADRN is 0.93, meaning the model has a good capability to distinguish between quality and defective fibers. An AUC of 0.93 reflects the model's moderate to strong predictive accuracy, suggesting that ESMA-ADRN effectively supports QC by reliably detecting imperfections in electrospun nanofiber images.

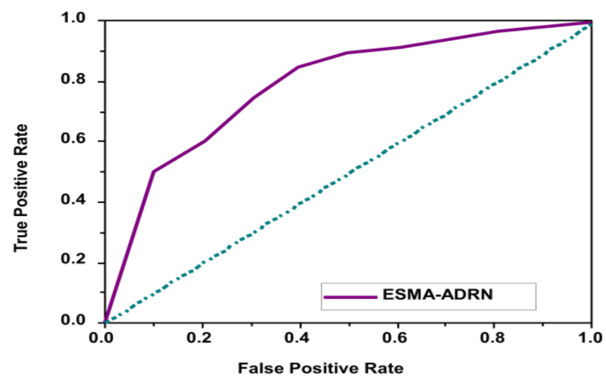

Fig. 3 – ROC curves and the associated AUC values of ESMA-ADRN

4.2 Accuracy

Measuring the accuracy of a model provides a broad evaluation of the model predict instances, where TP signifies true positives while TN stands for true negatives. According to the results, the model achieves the highest accuracy of 94.30% indicating that it classifies approximately 94 out of every 100 instances as ADR. This high accuracy shows that the model works well at the margin between positive and negative classes, which is useful when it comes to the issue of QC for electrospun nanofibers. The other models, including ESMA-ADRN100 and ESMA-ADRN80, also exhibit satisfactory accuracy measurements of 93.82 %and 93.40%, respectively, which asserts a reputable performance for all categories.

4.3 Precision

The positive predictive value, or the positive yield, evaluates the optimism, or the probability, that a positive result is correct. The contact detection accuracy rate is calculated as the ratio of true contacts to the total of true and false contacts. ESMA-ADR3N100, 80 estimates achieve the best precision of 96.58% meaning that almost all samples classified as positive by this model are indeed positive. Such high precision demonstrates the model's potential to separate true positive cases from false positives to minimize false alarms. Other examples including ESMA-ADRN100 and ESMA-ADRN100, 40 also possess the high precision value of 96.27% and 95.42% respectively.

4.4 Sensitivity

Sensitivity, also known as recall, will estimate the likelihood of the model in distinguishing between true positive items. As for the results, the model ESMA-ADR3N100, 80 showed the highest sensitivity of 0.93 while assessing a real proportion of positive cases in the general amount of positive samples. High sensitivity is important for cases where false negative results mean a positive case is missed with potentially grave repercussions. In the same context, another two models, namely ESMA-ADRN100 and ESMA-ADRN80, score high sensitivity at 92.34% and 91.78% respectively.

4.5 Specificity

It measures the extent to which models achieve precision on negative instances. It is defined as true negative over the total of true negative and all false positives. The percentage calculated in the model by using ESMA-ADRN100 is 93.12%, which is satisfactory in terms of the mechanism that has been developed to recognize negative cases. High specificity has major relevance mainly when the cost of taking an action positively on the false negative cases is higher. Other models, include ESMA-ADRN80 and ESMA-ADRN100, 40 which have close specificities of 92.58% and 91.45% respectively.

By comparing and contrasting the ESMA-ADRN models the performance of various parameters shows substantial progress in making the proposed ESMA-ADRN best suited for improving the QC of Electrospun nanofibers. The ESMA-ADR3N100, 80 model, gives the best result with 94.30% accuracy in the test dataset with the perfect division of positive and negative instances. The sensitivity and specificity measures are equal to 93.04% and 93.72% respectively, demonstrating a balanced performance of ESMA-ADRN. Also, the F-score of 94.77% proves acceptable if there is a high cost of both false negatives and false positives. Finally, as to the predictive accuracy, the MAE is 0.050 and the RMSE is 0.162, proving that the model is very close to the 'actual' outcome. Taken together, the above metrics tend to support the ESMA-ADRN framework as a means of improving the QC processes in the manufacture of electrospun nanofibers.

5. CONCLUSION

The major aim of this study was to design a reliable QC model of electrospun nanofibers through image analysis. It is critical to establish the credibility of the nanofiber scheme, crucial in the healthcare, filtration, as well as textile industries. The enhancements constituted in the proposed method, the ESMA-ADRN, higher precision in the quality assessments through methodological modulations in deep learning pertinent to image identification. The significant results of the ESMA-ADRN models can reaffirm, that, this approach can be efficient; the highest accuracy of 94.30% and precision of 96.58% is attained using the ESMA-ADR3N100, 80 model. This score of sensitivity 93.04% and specificity 93.72% reiterates the success of the model in picking out true positives while avoiding false positive results. In addition to the F – score of 94.77 %, the MAE and RMSE values of 0.050 and 0.162 respectively, lead to conclude that the predictions of the model are very close to the real values. The dataset used for training lacks diversity in nanofiber types and defect patterns, which may limit the generalizability of our proposed ESMA-ADRN model.

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Модель контролю якості електровідцентрових нанофібрових матеріалів на основі аналізу зображень

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Електровідцентровані нанофібри широко використовуються в інноваційних галузях, зокрема в біомедичній інженерії для каркасів тканин, фільтрації повітря та води, акумулюванні енергії тощо, завдяки високому співвідношенню площі поверхні до об'єму. Однак, серед основних проблем є відсутність точного контролю якості під час виробництва, що призводить до значних варіацій у властивостях та продуктивності матеріалу. У цій роботі запропоновано вирішення цієї проблеми шляхом розробки моделі ESMA-ADRN (Efficient Slime Mould Algorithm — оптимізована адаптивна глибока залишкова нейромережа) для оцінки якості нанофібрових структур на основі аналізу зображень. Для дослідження використовувався датасет зображень електровідцентрованих нанофібр, які проходили попередню обробку методом медіанного фільтрування для зменшення шуму. Виділення ознак проводилось за допомогою методу головних компонент (PCA) для вибору найбільш інформативного простору ознак. Результати моделі ESMA-ADRN перевершили інші моделі за всіма показниками, зокрема: – Точність (accuracy): 94,30%; – Прецизійність (precision): 96,58%; – Чутливість (sensitivity): 93,04%; – Специфічність (specificity): 93,72%; – F-міра: 94,77%. У перспективі подальші дослідження повинні охоплювати більше виробничих сценаріїв, а також передбачати тонке налаштування параметрів моделі для підвищення її ефективності у різних умовах виробництва.

Ключові слова: Електровідцентровані нанофібри, Контроль якості, Аналіз зображень, Глибока нейронна мережа, ESMA-ADRN, PCA.