Title Page:

Comparative Performance Evaluation of ResNet and innovative FNN (Feedforward Neural Network) for Synthetic Fiber Defect Detection in Textiles

Katta Narasimha Prasad[1],P Anandan[2]

Katta Narasimha Prasad[1],
Research Scholar,
Department of Computer Science Engineering,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University,Chennai,TamilNadu,India,Pincode:602105
192111091.sse@saveetha.com

P Anandan[2],
Project Guide,Corresponding Author,
Department of Nano Technology,
Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences,
Saveetha University,Chennai,TamilNadu,India,Pincode:602105
anandanp.sse@saveetha.com

Keywords: accuracy, defects, detection, dimensional irregularities, fabric, financial loss,FNN (Feedforward Neural Network), ResNet, synthetic fiber, textile, weaving.

ABSTRACT

Aim: The primary aim is to enhance ResNet's performance over FNN(Feedforward Neural Network) in the accurate detection of defects within synthetic fiber in textile materials.**Materials and Methods:**Two sets, ResNet and FNN (Feedforward Neural Network), each comprising 20 samples, were employed for the comparative analysis. Sample size calculations were conducted with an alpha value of 0.05 and 80% G-power. The analysis concentrated on evaluating accuracy, detecting defects, and identifying dimensional irregularities and weaving errors in ResNet and FNN materials for detecting synthetic fiber defects in textile materials to reduce financial loss.**Results:**In contrast to the 80.5190% accuracy achieved by the FNN(Feedforward Neural Network) classifier, the ResNet model exhibited a superior accuracy rate, reaching a maximum of 92.7380%. The comparison between these groups indicated a statistically significant variance via an Independent T-test analysis, displaying a p-value of 0.043 ($p<0.05$).**Conclusion:**In conclusion, considering constraints in resources and data, ResNet consistently outperforms the FNN (Feedforward Neural Network) approach across both sample groups.

Keywords: accuracy, defects, detection, dimensional irregularities, fabric, financial loss,FNN (Feedforward Neural Network), ResNet, synthetic fiber, textile, weaving.

INTRODUCTION

The textile industry grapples with ongoing challenges in recognizing imperfections within synthetic fiber materials, a pivotal concern impacting overall product quality. The precise detection of flaws(Sikka, Sarkar, and Garg 2022), encompassing dimensional irregularities and weaving inconsistencies, holds paramount importance in safeguarding textile integrity and performance. From subtle irregularities to more pronounced inconsistencies(Rafiei, Raitoharju, and Iosifidis n.d.2023), these defects significantly influence fabric quality and structural robustness. Conventional approaches often fall short in discerning these subtle distinctions, necessitating advanced technical solutions for accurate defect identification(Zhu et al. 2023). This research aims to revolutionize the identification of defects in synthetic fiber production, potentially mitigating financial losses associated with flawed processes in textile manufacturing. The research explores key aspects like accuracy, defect detection(D. Li et al. 2023), dimensional irregularities, and the role of advanced techniques in enhancing defect identification and minimizing financial losses in the textile and weaving industry.

Over recent years, substantial research has concentrated on refining the detection methods for synthetic fiber defects within textile materials. Upon thorough exploration of databases like IEEE Xplore, Springer, and Elsevier, an abundance of publications, comprising 471 articles on Science Direct and over 389 pieces on Google Scholar, have been dedicated to this facet of detection. The textile industry's classification of synthetic fibers hinges on quality gradation(C.

Li et al. 2021), distinguishing between first-grade fabric free of substantial defects and second-grade fabric bearing noticeable flaws. These imperfections account for considerable financial losses(Rasheed et al. 2020), with more than half of second-grade fabric production attributable to undetected flaws. Manual inspection methods, prone to human error and fatigue, manage to achieve only moderate accuracy rates ranging between 60% and 75%. Delayed flaw identification and manual inspection further impede production efficiency(Dlamini et al. 2021), resulting in additional financial losses. Nonetheless, strides in computer science and machine vision have ushered in automated fabric inspection(Kim and Lee 2024), heralding improved quality control. This inquiry focuses on fine-tuning algorithms for detecting dimensional irregularities and weaving flaws within synthetic fibers, significantly influencing defect identification and elevating fabric quality in textile manufacturing, thereby mitigating potential financial losses.

In the realm of textile defect detection, ResNet stands out as the premier performer, outshining even the captivating FNN (Feedforward Neural Network) in its quest for impeccable fabrics. While both deep learning techniques elegantly navigate the stage(Tong, Wong, and Kwong n.d.2017), ResNet's distinctive capability to comprehend intricate patterns and grasp long-range dependencies within fabric structures steals the spotlight. Its unrivaled precision in pinpointing dimensional irregularities and weaving flaws within synthetic fibers, particularly in elaborate weaves and complex patterns, solidifies ResNet's well-deserved standing ovation(Liu et al. n.d.2019). Consequently, the textile industry lauds ResNet for its superior accuracy and financial savings, acknowledging it as the true luminary of textile defect detection.

MATERIALS AND METHODS

This investigation transpired at the Data Analytics lab of Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences in Chennai, India, where a highly adaptable system facilitates precise research and meticulous results. The study's core comprised twenty participants, evenly divided into two groups: the ResNet ensemble and the FNN (Feedforward Neural Network) ensemble(Kumar and Pang n.d.2002). Stringent statistical rigor was maintained, ensuring a power level of 0.8 (beta), significance level of 0.05 (alpha), and a 95% confidence level. Additionally, the study's statistical robustness was fortified with an 80% G-Power value. With this resilient framework in place, the researchers aimed to ascertain whether ResNet's proficiency in pattern recognition and its capability to capture long-range dependencies within fabric structures could surpass the capabilities of FNN in detecting textile defects.

The primary goal of this research is to assess the identification of defects in synthetic fiber textiles using images from the "AITEX Fabric Image Database" dataset. This dataset includes essential variables of defects like broken end,dimensional irregularities,broken yarn,broken pick,warp ball, weft crack, Nep, and Knots, with the intention of improving accuracy in defect detection. Utilizing the preprocessed dataset that incorporates these diverse features(Zhou and Wang 2013), the ResNet algorithm is applied for the analysis of defect detection. The dataset comprises 245 images representing seven distinct fabric types, with 20 defect-free images for each type out of 140, while the remaining 105 images showcase various flaws. These images, sized at 4096 x 256 pixels, serve as the foundation for assessing defect detection in synthetic fiber textiles, emphasizing the importance of accuracy that is leading to financial loss in the textile and weaving industry.

The methodology employed in this research entailed the examination of a particular dataset and comparing its results with the well-established EfficientNet algorithm. This dataset, organized as an image dataset, contains a varied range of data values. To ensure a thorough analysis and comparison(Huang, Jing, and Wang n.d.2021), the dataset underwent careful examination using the algorithms outlined in this study. The hardware configuration involved an Intel dual-core processor with 8 GB of RAM. Using Jupyter Notebook, Python, and a MySQL database, the software setup provided a stable platform for executing the algorithm and facilitating the comparative analysis.

Resnet

ResNet, short for Residual Networks, represents an innovative architectural design that effectively addresses the vanishing gradient problem in deep learning through its unique skip connections. This distinctive feature empowers ResNet to explore intricate patterns within textile images, making it a robust choice for identifying defects in synthetic fiber textiles. Through the integration of dense layers and the utilization of its comprehension of complex correlations, ResNet excels in recognizing dimensional irregularities and flaws in fabric weaves. Trained on fabric image databases and employing loss functions like mean squared error, the model undergoes thorough evaluation on independent datasets to ensure its accuracy and efficacy in identifying textile faults, thereby minimizing potential financial losses attributed to defective fabric production.

FNN(Feedforward Neural Network)

FNN (Feedforward Neural Network), characterized by its innovative scaling technique, provides a well-balanced network design that optimally adjusts depth, width, and resolution. This strategic approach ensures both efficiency and accuracy in detecting defects within textile materials. Employing compound scaling, FNN achieves enhanced computational efficiency while maintaining robust performance in identifying dimensional irregularities and flaws in synthetic fiber weaves. Trained on fabric image datasets and guided by a suitable loss function like mean squared error, FNN's effectiveness is meticulously evaluated across diverse datasets to assess its capability in defect detection and reducing potential financial losses in the textile industry. Enriched with dense layers, the FNN model adeptly learns complex fabric structures, ensuring a detailed analysis of defects and a high level of accuracy in fault identification within textile imagery.

Statistical Analysis

In the comparison between ResNet and FNN (Feedforward Neural Network), ResNet is designated as the dependent variable, while FNN is positioned as the independent variable, maintaining this arrangement throughout the evaluation of their effectiveness and performance. In the analytical process, SPSS (Statistical Product and Service Solutions) version 26 generates graphs and facilitates regression analysis, t-tests, mean comparisons, and group statistics, focusing on parameters such as accuracy counts, mean values, standard error, and standard mean error(Xie 2008) . The analysis encompasses tables for mean equality tests, Levene's variance equality tests, and an accuracy bar graph. On the visual representation, the Y-axis illustrates mean accuracy, while the X-axis showcases diverse algorithm parameters.

RESULTS

The accuracy of raw data for both ResNet and FNN (Feedforward Neural Network) is presented in Table 1, each comprising 20 samples. Table 2 displays standard deviations of 2.14472 and 8.04828, standard error mean values of 0.67822 and 2.54509, and mean accuracy rates of 92.7380% and 80.5190% for ResNet and FNN, respectively, with an N of 20.

Table 3 illustrates the T-test outcomes for mean equality, conducting a two-tailed independent test, revealing an "F" value of 4.741 assuming equal variances. The 95% confidence intervals, assuming equal variances and without that assumption, unveil ranges of 17.75263 to 18.06673 in the upper case and 6.68537 to 6.37127 in the lower case. Figure 1 depicts a bar graph plotting groups on the X-axis and mean accuracy on the Y-axis, distinctly showing ResNet's superiority over FNN with a value of 0.043 ($p<0.05$) for single-tailed analysis.

DISCUSSION

The research outcomes indicate that for synthetic fiber defect detection, the mean accuracy of the FNN (Feedforward Neural Network) model is 80.5190%, whereas the ResNet classifier achieves a higher accuracy rate of 92.7380%. This underscores ResNet's superior performance compared to FNN in the detection of synthetic fiber defects. Through the use of an Independent T-test, the obtained p-value of 0.043 ($p<0.05$) further underscores ResNet's enhanced efficacy over FNN in accurately identifying defects in textile materials.

The dataset encompasses a comprehensive array of textile flaws, addressing dimensional irregularities and weaving defects in synthetic fibers, providing insights into texture, color variations, and tensile strength, as well as surface imperfections. This dataset aims to bridge the gap between textile stakeholders and decision-makers(Amor, Noman, and Petru 2021), assisting in production and investment strategies within the industry. ResNet and FNN, as powerful deep learning approaches, play a pivotal role in synthetic fiber defect detection. ResNet's architecture, characterized by deep-layered networks and skip connections, excels in capturing intricate patterns, particularly in identifying flaws like dimensional irregularities and weaving defects. Despite FNN (Feedforward Neural Network)'s advantages, ResNet's robustness and superior accuracy, reaching 92.7380% compared to FNN (Feedforward Neural Network)'s 80.5190%, establish it as the preferred choice for intricate visual tasks in detecting synthetic fiber defects, thereby mitigating potential financial losses associated with substandard fabric production.

Limitations observed in the assessment were specific to FNN (Feedforward Neural Network), particularly regarding model efficacy in dealing with defect diversity, uncertain adaptability across fabric types, and the substantial need for abundant labeled data. Additionally, complexities in deployment and unexplored scenarios emerged as challenges. However, throughout these limitations, ResNet consistently demonstrated superiority in synthetic fiber defect detection, positioning it as a more reliable choice in addressing accuracy, defects, and dimensional irregularities in the textile and weaving sector, thereby mitigating potential financial losses.

CONCLUSION

In conclusion, the evaluation of ResNet and FNN (Feedforward Neural Network) for synthetic fiber defect identification reveals ResNet's dominance over FNN. ResNet attained a mean accuracy of 92.7380%,surpassing FNN (Feedforward Neural Network)'s 80.5190%.This finding highlights ResNet's advanced feature extraction and deeper architecture with 0.043($p<0.05$) in accurately identifying synthetic fiber defects, solidifying its role as a potent solution for addressing accuracy, defects, and dimensional irregularities in textile and weaving scenarios, demonstrating significant performance and a more effective impact on minimizing financial losses.

DECLARATION

Conflict of Interest

This declaration affirms the absence of any reported conflicts of interest. To maintain our commitment to academic integrity and prevent inadvertent entanglement in matters related to academic honesty, we rigorously ensured the authenticity of our work.

Authors Contribution

KNP actively participated in data collection, data analysis, and manuscript composition. On the other hand, PA made substantial contributions to the conceptualization of the research idea and provided valuable feedback throughout the manuscript review process.

Acknowledgments

The indispensable support and resources provided by the esteemed Saveetha Institute of Medical and Technical Sciences were crucial to the feasibility of this research. The authors express deep gratitude for the invaluable assistance received from this respected institution.

Funding

Crucial financial support from the following institutions significantly contributed to the successful completion of our research. We extend sincere appreciation for their invaluable contributions to our scientific pursuits:

1. Saveetha Institute of Medical And Technical Sciences
2. Saveetha School of Engineering
3. Saveetha University

REFERENCES

Amor, Nesrine, Muhammad Tayyab Noman, and Michal Petru. 2021. "Classification of Textile Polymer Composites: Recent Trends and Challenges." *Polymers* 13 (16): 2592.

Dlamini, Sifundvolesihle, Chih-Yuan Kao, Shun-Lian Su, and Chung-Feng Jeffrey Kuo. 2021. "Development of a Real-Time Machine Vision System for Functional Textile Fabric Defect Detection Using a Deep YOLOv4 Model." *Textile Research Journal*, September. https://doi.org/10.1177/00405175211034241.

Huang, Yanqing, Junfeng Jing, and Zhen Wang. n.d. "Fabric Defect Segmentation Method Based on Deep Learning." Accessed January 12, 2024. https://ieeexplore.ieee.org/abstract/document/9312748.

Kim, Deageon, and Dongoun Lee. 2024. "Fabric Defect Detection Based on Artificial Intelligence." *International Journal of Intelligent Systems and Applications in Engineering* 12 (5s): 01–07.

Kumar, A., and G. K. H. Pang. n.d. "Defect Detection in Textured Materials Using Gabor Filters." Accessed January 12, 2024. https://ieeexplore.ieee.org/abstract/document/993164.

Li, Chao, Jun Li, Yafei Li, Lingmin He, Xiaokang Fu, and Jingjing Chen. 2021. "Fabric Defect Detection in Textile Manufacturing: A Survey of the State of the Art." *Security and Communication Networks* 2021 (May). https://doi.org/10.1155/2021/9948808.

Li, Dazi, Yi Ru, Zhudan Chen, Caibo Dong, Yining Dong, and Jun Liu. 2023. "Accelerating the Design and Development of Polymeric Materials via Deep Learning: Current Status and Future Challenges." *APL Machine Learning* 1 (2): 021501.

Liu, Juhua, Chaoyue Wang, Hai Su, Bo Du, and Dacheng Tao. n.d. "Multistage GAN for Fabric Defect Detection." Accessed January 12, 2024. https://ieeexplore.ieee.org/abstract/document/8937049.

Rafiei, Mehdi, Jenni Raitoharju, and Alexandros Iosifidis. n.d. "Computer Vision on X-Ray Data in Industrial Production and Security Applications: A Comprehensive Survey." Accessed January 12, 2024. https://ieeexplore.ieee.org/abstract/document/10005308.

Rasheed, Aqsa, Bushra Zafar, Amina Rasheed, Nouman Ali, Muhammad Sajid, Saadat Hanif Dar, Usman Habib, Tehmina Shehryar, and Muhammad Tariq Mahmood. 2020. "Fabric Defect Detection Using Computer Vision Techniques: A Comprehensive Review." *Mathematical Problems in Engineering* 2020 (November). https://doi.org/10.1155/2020/8189403.

Sikka, Monica Puri, Alok Sarkar, and Samridhi Garg. 2022. "Artificial Intelligence (AI) in Textile Industry Operational Modernization." *Research Journal of Textile and Apparel* ahead-of-print (ahead-of-print). https://doi.org/10.1108/RJTA-04-2021-0046.

Tong, Le, W. K. Wong, and C. K. Kwong. n.d. "Fabric Defect Detection for Apparel Industry: A Nonlocal Sparse Representation Approach." Accessed January 12, 2024. https://ieeexplore.ieee.org/abstract/document/7857011.

Xie, Xianghua. 2008. "A Review of Recent Advances in Surface Defect Detection using Texture analysis Techniques." *ELCVIA: electronic letters on computer vision and image analysis*, 1–22.

Zhou, Jian, and Jun Wang. 2013. "Fabric Defect Detection Using Adaptive Dictionaries." *Textile Research Journal*, February. https://doi.org/10.1177/0040517513478451.

Zhu, Qinmiao, Jingyun Chang, Teng Liu, Yuhui Wang, and Hua Yang. 2023.

“Transformer-Based Visual Inspection Algorithm for Surface Defects.” *Organizational Ethics: Healthcare, Business, and Policy: OE* 62 (9): 094102.

TABLES AND FIGURES

Table 1: The ResNet algorithm achieves an accuracy of 92.7380%, surpassing the FNN (Feedforward Neural Network) algorithm, which attains 80.5190% accuracy. In accuracy terms, ResNet outperforms FNN.

SAMPLE NO.	RESNET(%)	FNN(%)
1.	91.11	60.74
2.	88.15	80.74
3.	91.11	85.93
4.	94.81	85.19
5.	94.07	85.93
6.	92.59	82.22
7.	94.81	84.44
8.	92.59	81.48
9.	93.33	72.59
10.	94.81	85.93
11.	91.11	80.75
12.	88.15	60.73
13.	91.11	85.15
14.	92.59	85.97
15.	94.07	82.26
16.	94.81	85.89
17.	94.81	84.48
18.	93.33	81.44
19.	92.59	85.96
20.	94.81	72.56
Average	**92.7380**	**80.5190**

Table 2: The FNN (Feedforward Neural Network) achieves a mean accuracy of 80.5190%, accompanied by a standard deviation of 8.04828. In contrast, ResNet exhibits a mean accuracy of 92.7380% with a standard deviation of 2.14472.

Group Statistics					
Accuracy	Group	N	Mean	Std.Deviation	Std.Error Mean
	ResNet	20	92.7380	2.14472	0.67822
	FNN	20	80.5190	8.04828	2.54509

Table 3: The T-test for independent samples was conducted to assess the comparison between the accuracy groups. The outcomes, presented in the table, reveal the t-test for equal means and Levene's test for equal variances (F=4.741, sig=0.43).

Independent Samples test											
		Levene's Test for Equality of Variances		T-test for Equality of means							
		F	Sig.	t	df	Significance		Mean Difference	Std. Error Difference	95%Confidence Interval of the Difference	
						1-sided p	2-sided p			Lower	Upper
ACCURACY	Equal variances assumed	4.741	.043	4.639	18	.000	.000	12.21900	2.63391	6.68537	17.75263
	Equal variances not assumed			4.639	10.272	.000	.001	12.21900	2.63391	6.37127	18.06673

Statistical Bar Graph

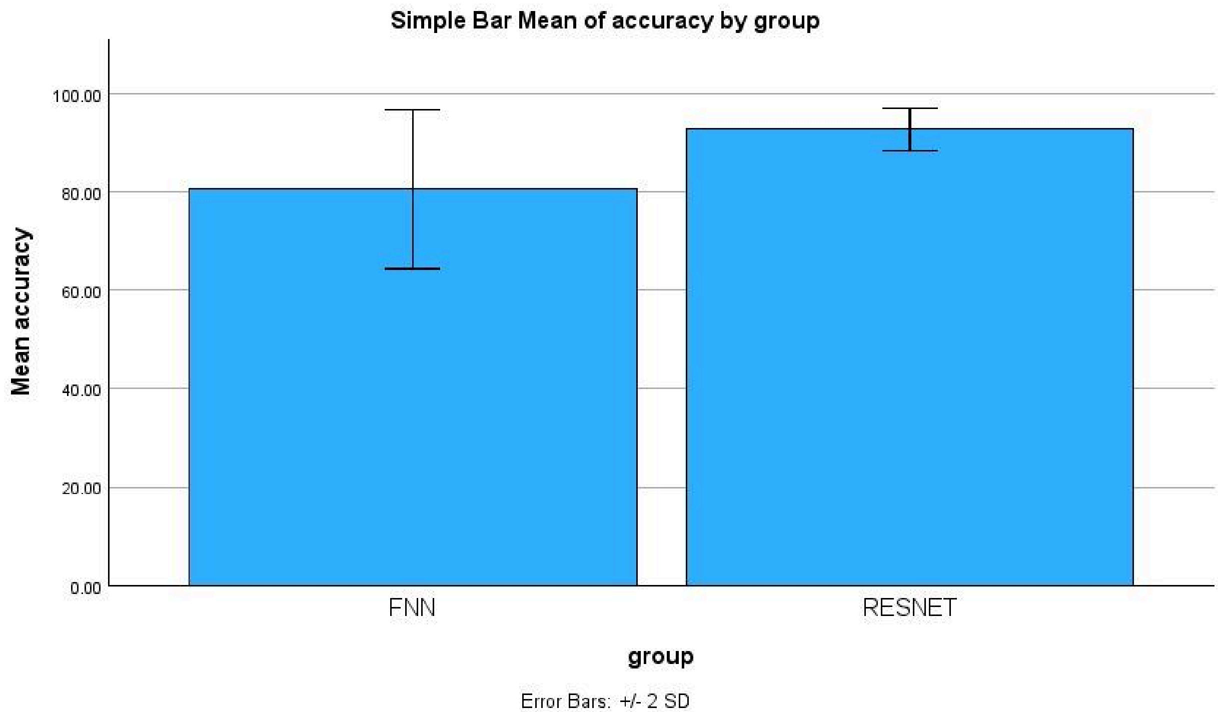

Fig 1: A remarkable contrast is apparent in the bar graph comparing ResNet and FNN (Feedforward Neural Network). The X-axis depicts ResNet and FNN, while the Y-axis demonstrates the mean with a variance of ± 1 standard deviation. ResNet notably exhibits a significantly higher mean compared to the values associated with FNN.