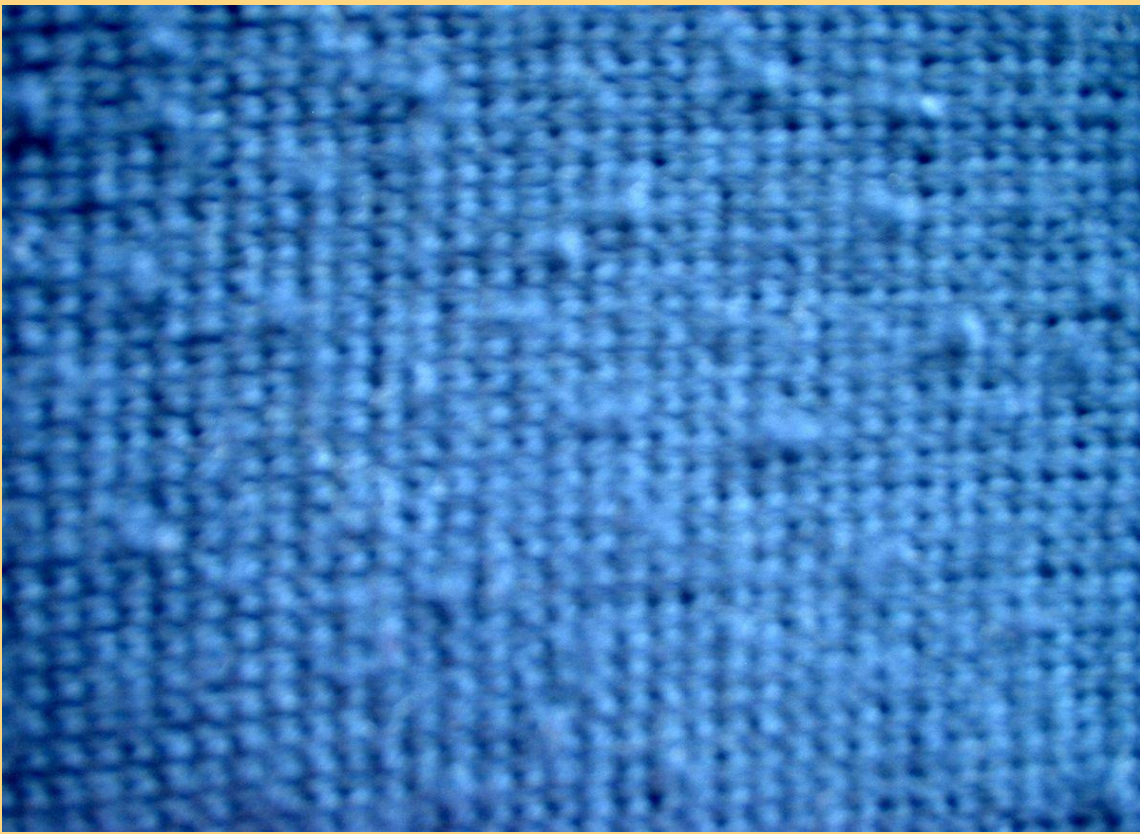


Detection of Synthetic Fiber Defects in Textiles using ResNet for Accurate Prediction in Comparison with LSTM(Long Short-Term Memory)

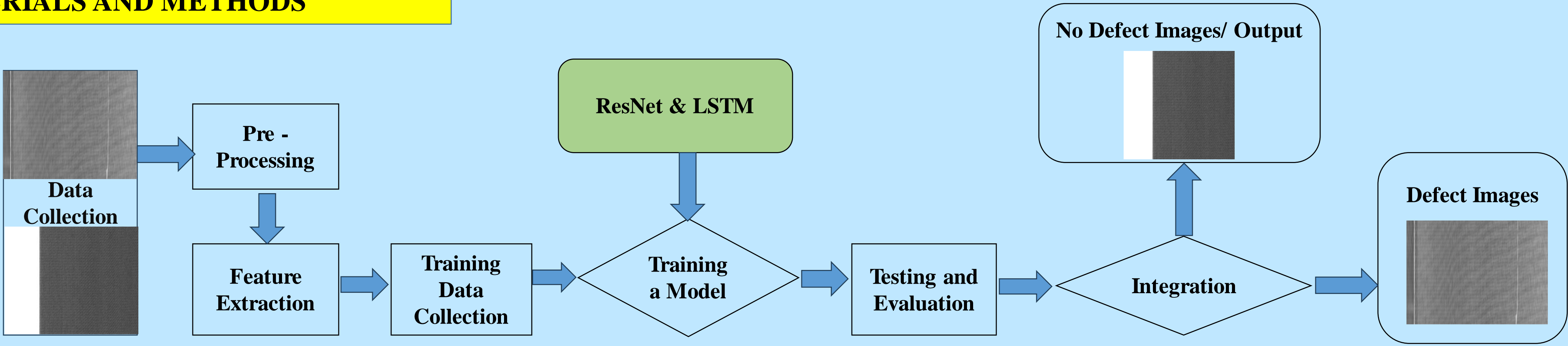
INTRODUCTION

- Detecting defects in synthetic fiber production is vital for textile manufacturers. It helps minimize financial losses and ensures customer satisfaction. Identifying defects like broken end, dimensional irregularities, broken yarn, holes, thin bars, thick bars, broken picks, warp balls, weft cracks, neps, and knots is essential for improving textile quality.
- This research study aims to compare the performance and accuracy of ResNet algorithm with LSTM for defect detection in order to improve the effectiveness of synthetic fiber defect detection techniques.
- The research findings suggest that ResNet algorithm surpasses LSTM in terms of defect detection in synthetic fiber production, making it a promising tool for reducing defects and ensuring high-quality fabrics.
- However, it is important to note that LSTM may face challenges in generalizing across different fabric types and may require a substantial amount of labeled data for accurate defect detection.
- By implementing ResNet or LSTM techniques, textile manufacturing companies can produce fabrics with reduced defects, thereby satisfying their customers' demands for superior quality textiles.
- ResNet algorithm outperforms LSTM in defect detection in synthetic fiber production, according to a research study, highlighting its potential as a valuable tool for manufacturers to reduce defects and improve the quality of fabrics.



Synthetic Fiber Defects in Textiles

MATERIALS AND METHODS



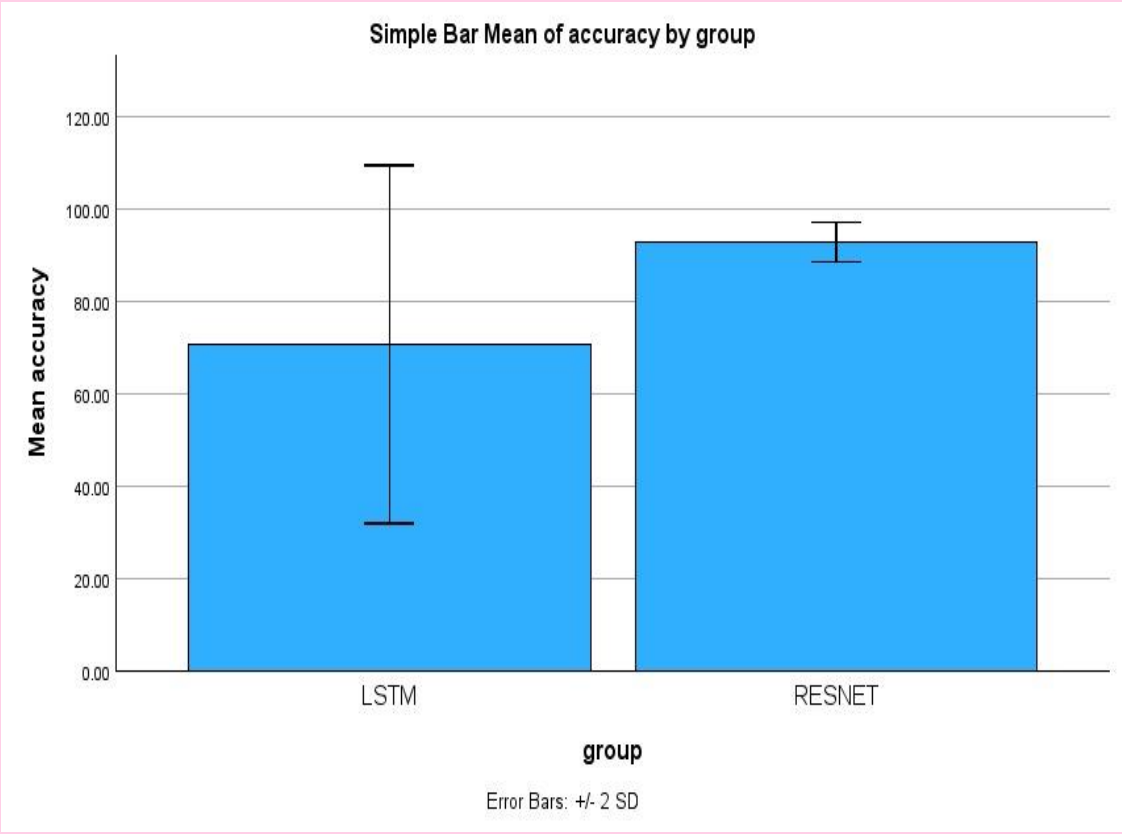
Synthetic Fiber Defect Detection in Textiles

RESULTS

- ResNet, a machine learning model, has a significantly higher accuracy rate of 92.73% when compared to LSTM's accuracy rate of 70.66% for identifying defects in synthetic fiber materials.
- The deeper architecture of ResNet allows it to extract high-level representations of the synthetic fiber images, enabling more accurate and reliable defect detection.
- The reason behind ResNet's effective identification of synthetic fiber defects is its advanced feature extraction capabilities and deeper architecture.
- The significant difference in performance between ResNet and LSTM highlights ResNet's far superior ability to detect and classify synthetic fiber defects.

Table presents Statistical Computation Values of Algorithms

Group Statistics					
A C C U R A C Y	Group	N	Mean	Std. Deviation	Std. Error Mean
	ResNet	20	92.7380	2.14472	0.67822
	LSTM	20	70.6660	19.39023	6.13173



Accuracy Comparison between LSTM and ResNet

DISCUSSION AND CONCLUSION

- The T-test statistical analysis revealed a significant difference between group 1 and group 2, with a p-value of 0.011 (independent sample T-test $p < 0.05$), indicating statistical significance.
- When comparing the performance of ResNet and LSTM algorithms in synthetic fiber defect detection, ResNet achieved an average accuracy of $2.1\% \pm SD$, while LSTM had an accuracy of $19.3\% \pm SD$, indicating that the performance of LSTM was comparatively lower.
- This capability of ResNet enables it to identify defects more accurately, contributing to improved quality control processes in the textile industry.
- It is worth noting that the LSTM algorithm faces challenges in capturing long-range dependencies and contextual information within sequential data, which affects its ability to detect synthetic fiber defects accurately.
- ResNet's excellence in quality control stems from its inherent ability to effectively analyze and process image data. By leveraging its deep residual network architecture, ResNet can identify and classify defects in synthetic fiber with remarkable accuracy.
- In conclusion, ResNet outperforms LSTM in synthetic fiber defect detection due to its ability to effectively capture spatial information and learn complex patterns from image data.

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