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Exploratory Data Analysis for Textile Defect Detection

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Abstract—The capacity to recognize anomalies in real-world visual data is essential for many computer vision uses. New approaches and ideas in unsupervised defective garments identification require data for training and evaluation. Understanding the constraints of the currently employed approach of human inspection is crucial for improving clothing quality. Uses for digital image processing in the textile sector are suggested. This method proposes a novel quantitative measuring strategy by fusing digital image processing with the Lab view platform. As this study progresses, it becomes clear that the FLDA yields the best results, with 95% accuracy, while the Hoeffiding Tree yields the lowest results, with 60% accuracy. When compared to other models, the FLDA's precision of 0.96 is the best you'll find, while the Hoeffiding Tree's is the lowest at 0.62. The FLDA provides the best result, with a recall value of 0.95, while the Hoeffiding Tree shows the lowest result, with a recall value of 0.60. The FLDA yields the best results (0.90 kappa value), whereas the Hoeffiding Tree yields the worst (0.20 kappa value).The FLDA exhibits the best results, with an F-Measure value of 0.95, while the Hoeffiding Tree displays the lowest results, with an F-Measure value of 0.58. The FLDA provides the best results, with an MCC value of 0.91, while the Hoeffiding Tree displays the worst results, with an MCC value of 0.22. The FLDA yields the best results (0.98 ROC value), whereas the Decision Table produces the worst results (0.69 ROC value). The best prediction accuracy is shown by the FLDA, at 0.98 of the PRC value, while the worst is shown by the Decision Table, at 0.67. The MAE is lowest (0.07) for the FLDA and highest (0.39) for the Hoeffiding Tree. The MAE deviation of the Bayes Net is 0.19. The best result is shown by the FLDA, with an RMSE of 0.22, while the largest RMSE deviation is found in the Hoeffiding Tree, at 0.62. The RMSEdeviation for Bayes Net is 0.41. The finest RAE is shown by the FLDA, at 13.39%, while the largest RAE deviation is 78.28% for the Hoeffiding Tree. The Bayes Net explains 38.74% of the variation in RAE. The best result is shown by the FLDA, with an RRSE of 44.36%; the largest RRSE variation is shown by the Hoeffiding Tree, with 123.99%. When compared to other models, the IBK's preparation time of 0 seconds is by far the shortest. While the Bayes Net completes its task in 0.03 seconds, FLDA can take up to 0.17 seconds. The FLDA model is found to have superior performance in this study.

Keywords- FLDA;Ada Boost; Hoeffiding Tree; IBK; Bayes Net;

I. INTRODUCTION

Digital image processing technology is a recent innovation in computer science that uses computers and other digital technologies to process photos to help humans recognise and extract useful data. This technology reproduces images more accurately, adaptably, and versatilely than older, more laborious ways. Since the late 1980s, computer technology has enabled digital image processing in textile and garment inspection. This algorithm outperforms manual detection in clothing detection, categorization, and evaluation. It employs digital image processing to check garments for defects, flatness, and style without the drawbacks of tactile inspection. We utilise Labview to process and measure computer-generated digital images. When applied with neural networks, support vector machines, deep learning, and other technologies, it improves apparel photo recognition and categorization. This paper is organized into four sections: relevant works, materials and methods, results and discussions, and conclusions.

II. LITERATURE REVIEW

All nations today prioritise environmental conservation and green technology. The coloured cotton as a promising study because it is a green product.[1-5] China produced 33% of the world's coloured cotton in 2001. China makes 16% of coloured cotton. China produces most coloured cotton. However, all Chinese coloured cotton research is still in its infancy and needs to be done.[6-8]. Since the optical fibre terminal is more

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important in the optical fibre communication system, its quality requirements are rising. The current detection method relies on manual magnification and size and contour detection.[9-10] Due of its low detection efficiency and precision, it values its detectors' skill. Society struggles when automation increases.[11] Due to its high cost, bulkiness, and poor operability, enhanced testing equipment is not commonly used.Thus, a new generation of efficient and effective optical fibre terminal detecting devices is needed.[13] Humans have always wanted to shield themselves against cold or heat.[14] Fabrics were previously a luxury, but mass manufacture and consumption made them essential. Clothing evolved alongside society, politics, religion, and morals [15-18]. After the Industrial Revolution and technological advances, few people need to know how to spin or weave, but they do need to know how to evaluate the durability of machine-made materials.[19-20] Fibre identification and textile research are increasingly crucial for textile producers and end consumers.[21] Experience and practise help some people identify fabric quality, but "learning by making mistakes" is time-consuming, stressful, and expensive. Computer vision difficulties were handled. It's let users customise and automate many tasks. For example, in textiles.[22] Some articles utilise this information to classify textile fibres, flat textiles, defects, and inspections. Using PCA and fuzzy clustering, identified fabric structure autonomously.[23] Local Binary Patterns and Gray-Level Cooccurence Matrix-trained ANNs discovered fabric defects.Using a biological vision model, [24] created a textile fault detection method. [25] Pioneered automatic fabric fault identification using lattice segmentation and templates. [26] used autoencoders to identify fabric defects. Despite having 19,894 images, the writers used a CNN to recognise fabrics. This article proposes a new textile categorization approach. According to Transfer Learning, the CNN extracts features.[27-30]. Five classifiers analysed deep extractors. Vision-based categorization is complex and requires fast calculations. Each classifier was evaluated using accuracy (Acc) and F1-Score (F1S). We considered data extraction and classification times.

Museums employ a digital service platform for cultural relic study, storage, management, and display.[31-33]. This new cultural asset conservation and usage paradigm has arisen in the setting of ever-changing digital technology. Digitising museum resources is being studied extensively.[34-36] Cloud computing and digital museums are examined. Museums employ digital technologies to manage cultural treasures.[37] Cultural relics, warehouse, expert, and flow information are also harmonised.[38] The digital record, exhibition, and transmission of cultural relics at the Liangzhu Museum are examined in this study to introduce the digital construction mode of museums.[39-40]

Textile inspection has used increasingly sophisticated digital image processing since the 1980s. Some academics employ digital image processing technologies to examine defects, flatness, feature detection, and clothing style classification. Digital image processing technology detects and classifies clothes more objectively and cheaply than human detection methods.

III. MATERIALS AND METHODS

This section governs that the materials and methods of this research work. The dataset, namely, textile defect detection, was collected from the reputed and large Kaggle data repository. The collected image dimensions are 32x32 or 64x64, and the diversity of the textile images is good in terms of colour, cut, hole, thread, and metal contamination. This work governs only holes and extra threads in the horizontal and vertical positions of the clothes.

The following selected algorithms are implemented to fit a model by 90:10 cross validation techniques in Weka.3.9.5.tool.

- Bayes Net
- FLDA
- IBK
- AdaBoostM1
- Decision Table
- Hoeffding Tree

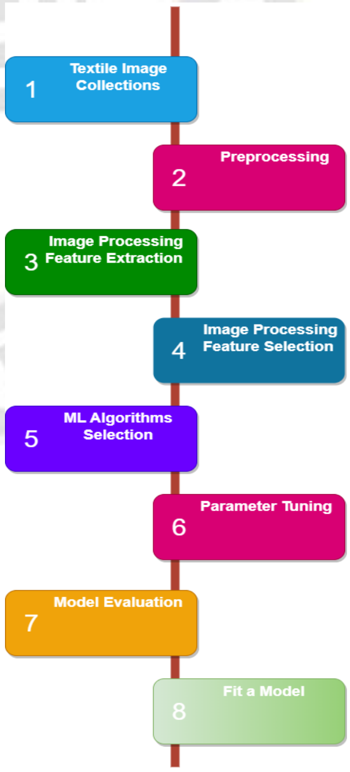

Fig 1: Flow Process for making models

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Table 1: Models and their outcome

S.No	Model	Accuracy	Precision	Recall
1	Bayes Net	80%	0.81	0.8
2	FLDA	95%	0.96	0.95
3	IBK	70%	0.71	0.7
4	AdaBoostM1	75%	0.75	0.75
5	Decision Table	75%	0.75	0.75
6	Hoeffiding Tree	60%	0.62	0.6

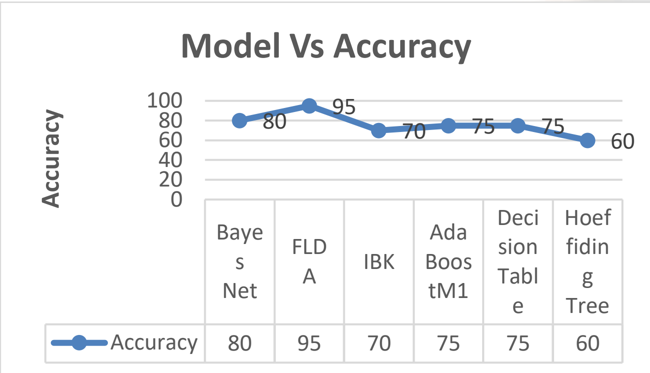

Fig 2: Model Vs Accuracy

As can be seen in Figure 2, the FLDA yields the best results (95%) while the Hoeffiding Tree yields the worst (60%) when compared to other models. Equally accurate at 75% are Ada Boost and Decision Table. The accuracy of the Bayes Net is 80%.

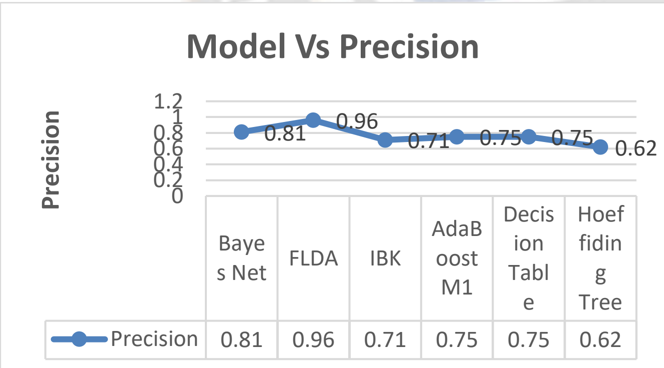

Fig 3: Model Vs Precision

As can be seen in Figure 3, the FLDA yields the highest precision (0.96); the Hoeffiding Tree, on the other hand, yields the lowest (0.62). In terms of accuracy, both the Ada Boost and the Decision Table score a 0.75.The Bayes Net achieves an accuracy of 0.81.

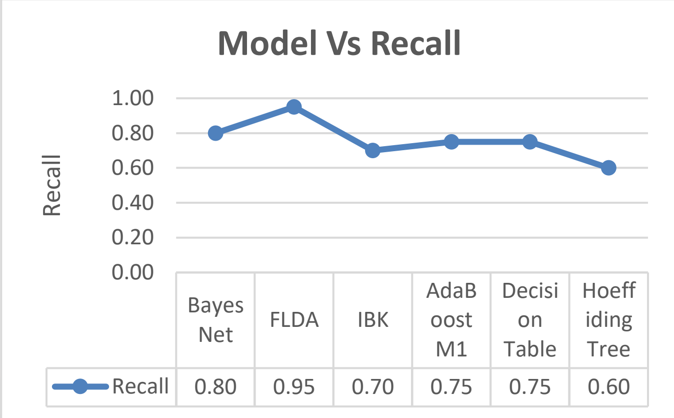

Fig 4: Model Vs Recall

Figure 4 illustrates that, compared to other models, the FLDA produces the best results (0.95 recall), while the Hoeffiding Tree produces the worst results (0.60 recall). Recall values of 0.75 are achieved by both the Ada Boost and the Decision Table. The recall value of the Bayes Net is 0.80

Table 2: Models and their statistical outcome

S.No	Classifier	Kappa	F-Measure	MCC
1	Bayes Net	0.6	0.8	0.61
2	FLDA	0.9	0.95	0.91
3	IBK	0.4	0.7	0.41
4	AdaBoostM1	0.5	0.75	0.5
5	Decision Table	0.5	0.75	0.5
6	Hoeffiding Tree	0.2	0.58	0.22

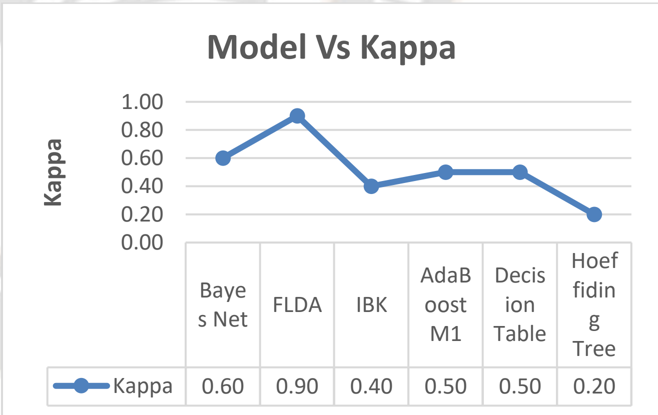

Fig 5: Model Vs Kappa

Figure 5 above depicts that the FLDA displays the best outcome, with a kappa value of 0.90, while the Hoeffiding Tree exhibits the worst conclusion, with a kappa value of 0.20. The kappa for both the Ada Boost and the Decision Table is 0.50.The kappa value of the Bayes Net is 0.60.

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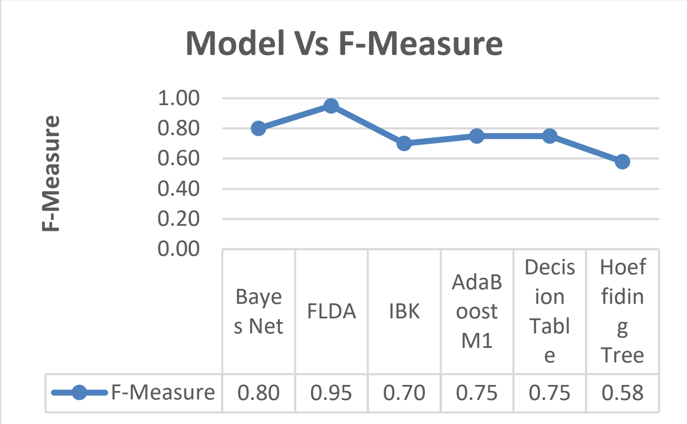

Figure 6: Model Vs F-Measure

Figure 6 illustrates that, when compared to the other models, the FLDA yields the greatest results (0.95 of F-Measure value), while the Hoeffiding Tree yields the lowest results (0.58 of F-Measure value). The F-Measure for both the Ada Boost and the Decision Table is 0.75.Bayes's network has an F-measure of 0.80.

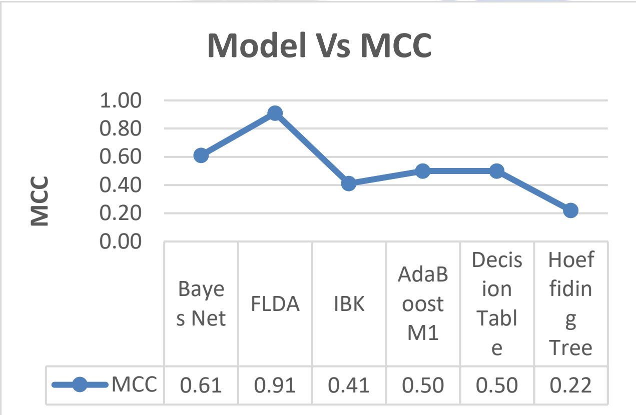

Fig 7: Model Vs MCC

Figure 7 indicates that when compared to other models, the FLDA yields the best results (0.91 MCC value), while the Hoeffiding Tree yields the worst results (0.22 MCC value). The MCC for both the Ada Boost and the Decision Table is 0.50.The MCC of the Bayes Net is 0.61.

Table 3: Models and their ROC and PRC

S.No	Classifier	ROC	PRC
1	Bayes Net	0.82	0.829
2	FLDA	0.98	0.98
3	IBK	0.7	0.64
4	AdaBoostM1	0.86	0.88
5	Decision Table	0.69	0.67
6	Hoeffiding Tree	0.84	0.81

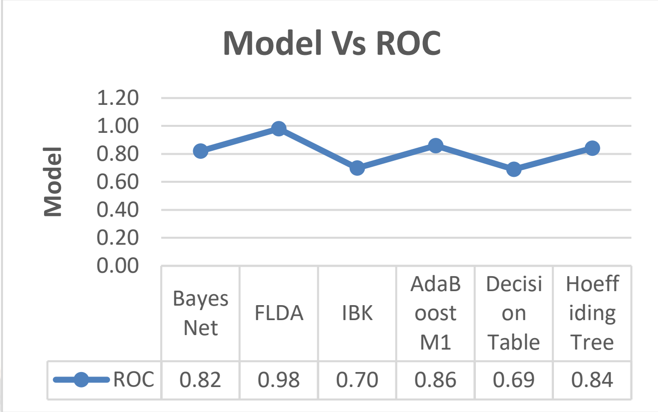

Fig 8: Model Vs ROC

Figure 8 demonstrates that when compared to the other models, the FLDA yields the greatest results (0.98 ROC value), while the Decision Table yields the lowest results (0.69 ROC value). Ada's Boost has a ROC of 0.86. Both the Bayes Net and the Hoeffiding Tree have ROC values of 0.82.

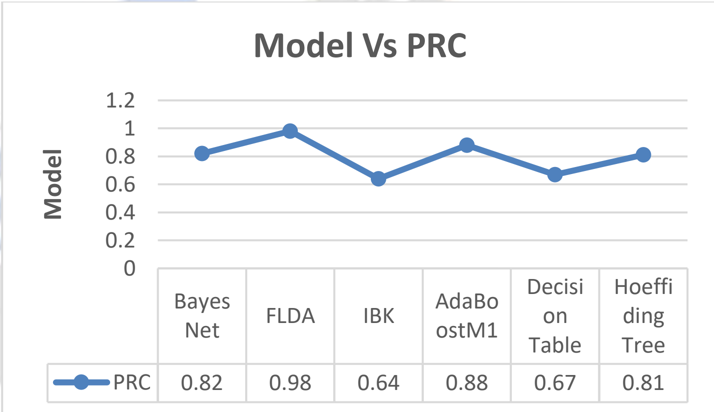

Fig 9: Model Vs PRC

Figure 9 demonstrates that when compared to the other models, the FLDA yields the best results (0.98 of the PRC value), while the Decision Table yields the lowest results (0.67 of the PRC value). In terms of PRC, the Ada Boost is 0.88. There is a 0.82 PRC difference between the Bayes Net and the Hoeffiding Tree.

Table 4: Models and their Deviations

S.No	Classifier	MAE	RMSE	RSE	RRSE
1	Bayes Net	0.19	0.41	38.74%	81.68%
2	FLDA	0.07	0.22	13.39%	44.36%
3	IBK	0.32	0.52	64.00%	104.40%
4	AdaBoostM1	0.25	0.5	49.70%	99.25%
5	Decision Table	0.34	0.46	67.92%	91.37%
6	Hoeffding Tree	0.39	0.62	78.28%	123.99%

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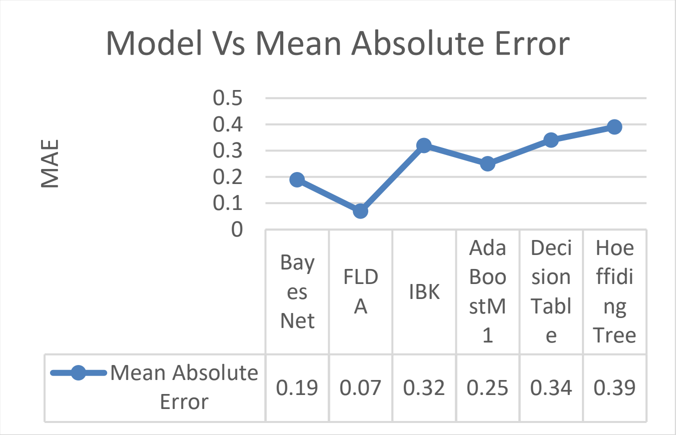

Fig 10: Model Vs MAE

Figure 10 demonstrates that the best result can be seen with the FLDA, with an MAE of 0.07, while the highest deviation can be seen with the Hoeffiding Tree, at 0.39. The Bayes Net has a standard deviation of 0.19. There's a discrepancy of 0.32 on the IBK. The Ada Boost has a divergence of 0.25, while the Decision Table deviates by 0.34.

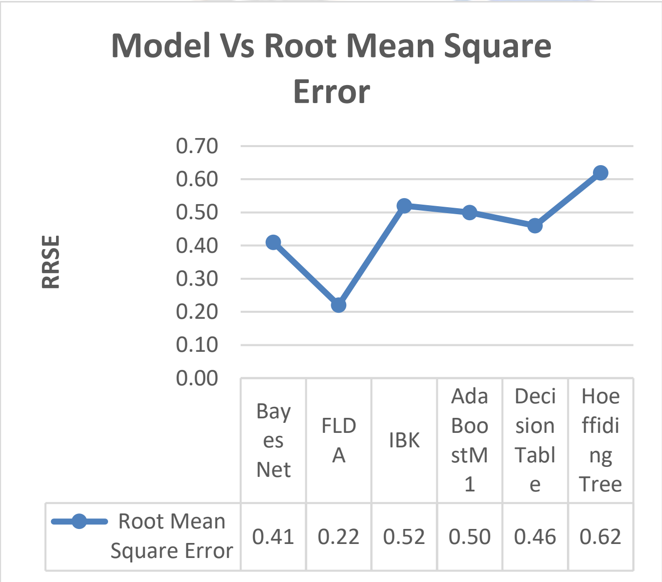

Fig 11: Model Vs RMSE

Figure 11 demonstrates that the FLDA yields the best results (RMSE = 0.22), whereas the Hoeffiding Tree yields the greatest variance (RMSE = 0.62). A deviance of 0.41 is seen in the Bayes Net. Variation in the IBK is 0.52. The Ada Boost deviates from the mean by 0.50, whereas the Decision Table deviates by 0.46.

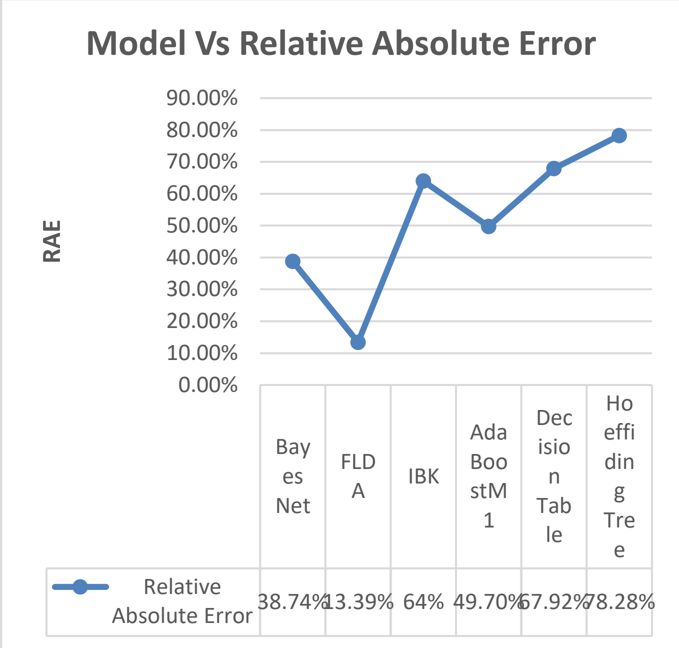

Fig 12: Model Vs RAE

Figure 12 demonstrates that the best RAE is achieved with the FLDA, at 13.39%, while the largest variation is 78.28% with the Hoeffiding Tree. The percentage of error for the Bayes Net is 38.74. 64% of the IBK is outside the norm. The standard deviation for the Ada Boost is 49.70%, whereas the standard deviation for the Decision Table is 67.92%.

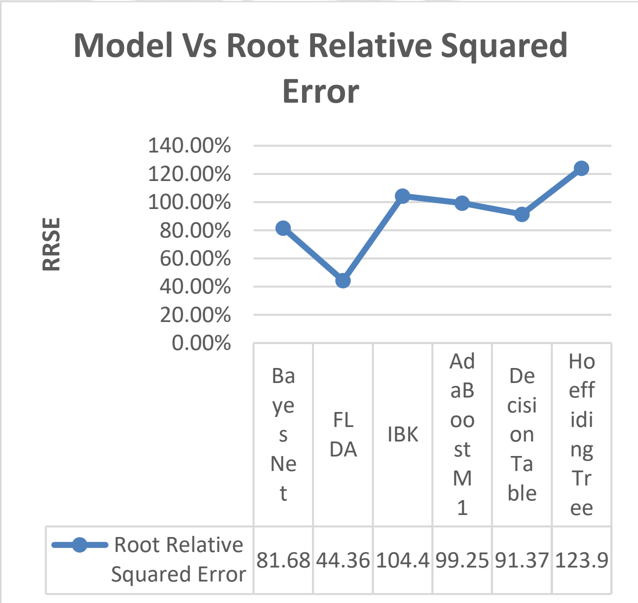

Fig 13: Model Vs RRSE

Figure 13 demonstrates that the FLDA yields the best results, with an RRSE of 44.36%, while the Hoeffiding Tree yields the most variation, at 123.99%. As a percentage, Bayes' Net is 81.68 percent off. The standard deviation of the IBK is

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104.40. Difference between the Ada Boost and the Decision Table is 91.25% and 91.37 %, respectively.

Table 5: Models and time consumption

S.No	Classifier	Time(In Seconds)
1	Bayes Net	0.03
2	FLDA	0.17
3	IBK	0.00
4	AdaBoostM1	0.05
5	Decision Table	0.02
6	Hoeffiding Tree	0.01

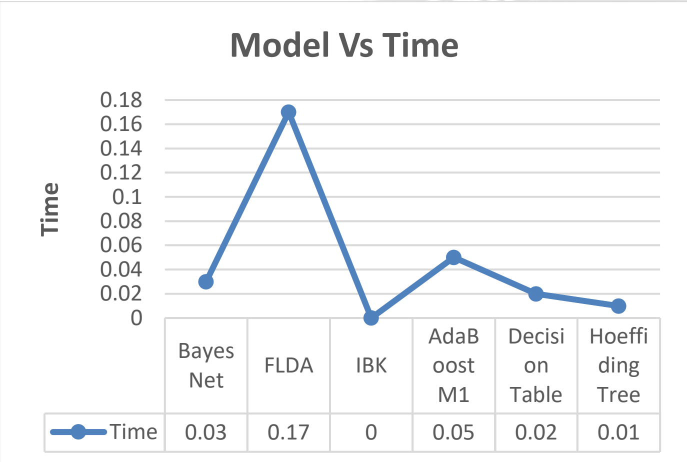

Fig 14: Model Vs Time

Figure 14 shows that the IBK requires no time at all to create their model, making it the fastest-to-create of all the models considered. It takes 0.03 seconds for a Bayes Net model to be created, 0.17 seconds for a FLDA model, 0.05 seconds for an Ada Boost model, 0.02 seconds for a Decision Table model, and 0.01 seconds for a Hoeffiding Tree model.

IV. CONCLUSION

This work concludes that the This quantitative measurement method uses digital image processing and Lab view. The FLDA has 95% accuracy, while the Hoeffiding Tree has 60%. The FLDA has the highest precision, 0.96, while the Hoeffiding Tree has the lowest, 0.62. The FLDA has 0.95 recall, while the Hoeffiding Tree has 0.60. The FLDA has 0.90 kappa value, while the Hoeffiding Tree has 0.20.The FLDA has the highest F-Measure value at 0.95, while the Hoeffiding Tree has the lowest at 0.58. The FLDA has 0.91 MCC, while the Hoeffiding Tree has 0.22 MCC. The FLDA has a 0.98 ROC value, while the Decision Table has 0.69. The FLDA has a PRC value of 0.98, while the Decision Table has 0.67. The FLDA yields the best MAE of 0.07, whereas the Hoeffiding Tree yields 0.39. Bayes Net MAE deviation is 0.19. FLDA has 0.22 RMSE, while Hoeffiding Tree has 0.62. Bayes Net RMSE deviation is 0.41. The FLDA has 13.39% RAE and the Hoeffiding Tree 78.28%. Bayes Net is 38.74% RAE deviation. The FLDA's 44.36% RRSE is best, while the Hoeffiding Tree's is 123.99%. The IBK model is the fastest to make at 0 seconds. Bayes Net takes 0.03 seconds, FLDA 0.17 seconds (maximum). This work recommended FLDA due to its performance compare than other models.

REFERENCES

[1] Paul Bergmann, Michael Fauser, David Sattlegger, Carsten Steger. MVTec AD - A Comprehensive Real-World Dataset for Unsupervised Anomaly Detection; in: IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2019.

[2] Jacintha and S. karthikeyan, “A survey on various fabric defect detection methods,” in 2019 International Conference on Communication and Signal Processing (ICCSP), April 2019, pp. 0801–0805.

[3] R. Divyadevi and B. V. Kumar, “Survey of automated fabric inspection in textile industries,” in 2019 International Conference on Computer Communication and Informatics (ICCCI), Jan 2019, pp. 1–4.

[4] X. Wang, N. D. Georganas, and E. M. Petriu, “Automatic woven fabric structure identification by using principal component analysis and fuzzy clustering,” in 2010 IEEE Instrumentation Measurement Technology Conference Proceedings, May 2010, pp. 590–595.

[5] O. Kaynar, Y. E. Is¸ik, Y. Gormez, and F. Demirkoparan, “Fabric defect detection with lbp-glmc,” in 2017 International Artificial Intelligence and Data Processing Symposium (IDAP), Sep. 2017, pp. 1–5.

[6] C. Li, G. Gao, Z. Liu, M. Yu, and D. Huang, “Fabric defect detection based on biological vision modeling,” IEEE Access, vol. 6, pp. 27 659– 27 670, 2018.

[7] L. Jia, J. Zhang, S. Chen, and Z. Hou, “Fabric defect inspection based on lattice segmentation and lattice templates,” J. Franklin Institute, vol. 355, no. 15, pp. 7764–7798, 2018.

[8] H. Tian and F. Li, “Autoencoder-based fabric defect detection with crosspatch similarity,” in 2019 16th International Conference on Machine Vision Applications (MVA), May 2019, pp. 1–6.

[9] X. Wang, G. Wu, and Y. Zhong, “Fabric identification using convolutional neural network,” in International Conference on Artificial Intelligence on Textile and Apparel. Springer, 2018, pp. 93–100.

[10] T. Grubinger, G. Chasparis, and T. Natschlager, “Generalized online transfer learning for climate control in residential buildings,” Energy and Buildings, vol. 139, pp. 63–71, 01 2017.

[11] C. Mazo, J. Bernal, M. Trujillo, and E. Alegre, “Transfer learning for classification of cardiovascular tissues in histological images,” Computer Methods and Programs in Biomedicine, vol. 165, 08 2018.

[12] H. K. Suh, J. IJsselmuiden, J. W. Hofstee, and E. J. van Henten, “Transfer learning for the classification of sugar beet and volunteer potato under field conditions,” Biosystems

Engineering, vol. 174, pp. 50 – 65, 2018. [Online].Available:http://www.sciencedirect.com/science/article/pii/S1537511016308777

[13] Q. Lin, J. Hong, Z. Liu, B. Li, and J. Wang, "Investigation into the topology optimization for conductive heat transfer based on deep learning approach," International Communications in Heat and Mass Transfer, vol. 97, pp. 103 – 109, 2018. [Online].

[14] Q. Wang, P. Du, J. Yang, G. Wang, J. Lei, and C. Hou, "Transferred deep learning based waveform recognition for cognitive passive radar," Signal Processing, vol. 155, pp. 259 – 267, 2019. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0165168418303256

[15] X. Li, H. Liu, P. Lv, and L. Liu, "Theoretical model for the motion of a ring spinning traveler," Journal of the Textile Institute, vol. 112, no. 3, pp. 1–11, 2020.

[16] Yahya Ghufran Khidhir, Ameer Hussein Morad. (2023). Real-Time End-to-End Self-Driving Car Navigation. International Journal of Intelligent Systems and Applications in Engineering, 11(2s), 366–372. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2732

[17] E. Owlia and S. A. Mirjalili, "The effect of launcher parameters on the projectile velocity in laboratory electromagnetic weft insertion system," Journal of the Textile Institute, vol. 112, no. 8, pp. 1–8, 2020.

[18] H. S. Khaddam and G. G. Ahmad, "A method to evaluate the diameter of carded cotton yarn using image processing and artificial neural networks," Journal of the Textile Institute, no. 3, pp. 1–10, 2021.

[19] Y. Shu, B. Li, D. Zuo, J. Zhang, and H. Gan, "Surface defect detection and recognition method for multi-scale commutator based on deep transfer learning," Arabian Journal for Science and Engineering, no. 7, pp. 1–12, 2021.

[20] W. Amir and A. Ahmed, "Applied vision about green marketing for trademark in the field of textile design and finishing," Journal of Design Sciences and Applied Arts, vol. 2, no. 1, pp. 85–99, 2021

[21] K. Parvesh, C. Tharun, and M. Prakash, "Apparel recommendation engine using inverse document frequency and weighted average Word2vec," Journal of Cognitive Human-Computer Interaction, vol. 1, no. 2, pp. 46–56, 2021.

[22] J. Li, D. Chen, N. Yu, Z. Zhao, and Z. Lv, "Emotion recognition of Chinese paintings at the thirteenth national exhibition of fines arts in China based on advanced affective computing," Frontiers in Psychology, vol. 12, Article ID 741665, 2021.

[23] A. Noor, M. A. Saeed, T. Ullah, Z. Uddin, and R. Khan, "A review of artificial intelligence applications in apparel industry," Journal of the Textile Institute, vol. 113, no. 3, pp. 1–10, 2021.

[24] F. Saad, A. Baffoun, B. Mahltig, and M. Hamdaoui, "Polyester fabric with fluorescent properties using microwave technology for anti-counterfeiting applications," Journal of Fluorescence, vol. 32, no. 1, pp. 327–345, 2021.

[25] B. Sharma, N. Kumari, S. Mathur, and V. Sharma, "A systematic review on iron-based nanoparticle-mediated clean-up of textile dyes: challenges and prospects of scale-up technologies," Environmental Science and Pollution Research, vol. 29, no. 1, pp. 312–331, 2021.

[26] P. Secim-Karakaya, P. Saglam-Metiner, and O. Yesil-Celiktas, "Antimicrobial and wound healing properties of cotton fabrics functionalized with oil in water emulsions containingpinus brutiabark extract and pycnogenol for biomedical applications," Cytotechnology, vol. 73, no. 3, pp. 423–431, 2021.

[27] Wang Wei, Natural Language Processing Techniques for Sentiment Analysis in Social Media , Machine Learning Applications Conference Proceedings, Vol 1 2021.

[28] M. Rahman, N. Cicek, and K. Chakma, "The optimum parameters for fibre yield (%) and characterization oftypha latifolia l.fibres for textile applications," Fibers and Polymers, vol. 22, no. 6, pp. 1543–1555, 2021.

[29] J Thambu Gladstan , Dr.E.Mohan. "Object Recognition Based on Wave Atom Transform," Research Journal of Applied Sciences, Engineering and Technology – Volume 8 ,issue 13, 1613-1617, 2014, ISSN: 2040-7459; e-ISSN: 2040-7467

[30] I. Z. Ansari and M. M. Mehadi, "An aesthetic approach of seamless garments: a review," Journal of Textile Engineering, vol. 1, no. 1, pp. 66–72, 2021.

[31] S. Wan, Y. Xia, L. Qi, Y. H. Yang, and M. Atiquzzaman, "Automated colorization of a grayscale image with seed points propagation," IEEE Transactions on Multimedia, vol. 22, no. 7, pp. 1756–1768, 2020.

[32] Dr. Antino Marelino. (2014). Customer Satisfaction Analysis based on Customer Relationship Management. International Journal of New Practices in Management and Engineering, 3(01), 07 - 12. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/26

[33] C. T. O'Neill, T. Proietti, K. Nuckols et al., "Inflatable soft wearable robot for reducing therapist fatigue during upper extremity rehabilitation in severe stroke," IEEE Robotics and Automation Letters, vol. 5, no. 3, pp. 3899–3906, 2020.

[34] M. Leone, "Digital cosmetics: a semiotic study on the Chinese and global meanings of the face in image-processing apps," Chinese Semiotic Studies, vol. 16, no. 4, pp. 551–580, 2020.

[35] T. D. P. Caldas, K. S. Augusto, J. C. Á. Iglesias, S. Paciornik, and A. L. A. Domingues, "Analysis of cracks and coating in iron ore pellets by digital image processing," REM-International Engineering Journal, vol. 73, no. 3, pp. 345–352, 2020.

[36] E.Mohan,Dr.C.Puttamadappa et.al ""Facial Tracking in Video Using Artificial Neural Networks", International Journal of Soft Computing 3(4):271-276, 2008.

[37] V. V. Kibitkin and A. I. Solodushkin, "Increasing measuring area of deformed solid by digital image correlation," Russian Physics Journal, vol. 64, no. 4, pp. 599–604, 2021.

[38] B. Jia and W. Zhang, "Application of digital image processing technology in online education under covid-19 epidemic," Journal of Intelligent and Fuzzy Systems, no. 2, pp. 1–7, 2021.

[39] S. Ahmad and S. Miskon, "A conceptual model of business intelligence system adoption for the textile and apparel industry in Pakistan," Mehran University Research Journal of Engineering and Technology, vol. 40, no. 2, pp. 251–264, 2021.

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[40] A. R. W. Sait, I. Pustokhina, and M. Ilayaraja, "Modeling of multiple share creation with optimal signcryption technique for digital image security," Journal of Intelligent Systems and Internet of Things, vol. 0, no. 1, pp. 26–36, 2019.

[41] M. Terzi, I. Kursun Unver, M. Cinar, and O. Ozdemir, "Digital image processing (dip) application on the evaluation of iron-rich heavy mineral concentrates produced from river sand using a sequential mineral processing approach," Physicochemical Problems of Mineral Processing, vol. 57, no. 3, pp. 21–35, 2021.

[42] C. Liu, "An enhanced cascaded beamformer based on overlapped subarrays," Signal, Image and Video Processing, vol. 16, no. 4, pp. 905–910, 2021.

[43] Rodriguez, L., Rodríguez, D., Martinez, J., Perez, A., & Ólafur, J. Leveraging Machine Learning for Adaptive Learning Systems in Engineering Education. Kuwait Journal of Machine Learning, 1(1). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/103

[44] S. Chakraborty and M. C. Biswas, "Impact of covid-19 on the textile, apparel and fashion manufacturing industry supply chain: case study on a ready-made garment manufacturing industry," SSRN Electronic Journal, vol. 3, no. 2, pp. 1–22, 2020