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Application of artificial intelligence in mechanical processing of cotton for ring and open end spinning

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Abstract : Major value addition of cotton is done through spinning of yarn and then converting it to fabric through knitting and weaving. Knitted fabric are then converted into mostly inner wear, T shirts and woven fabric are used in the manufacture of outer wear and home textiles. Quality of final garment and home textiles depends on the type of yarn used and its quality. Similarly, Yarn quality depends on the quality of its raw material that is cotton and also the process parameters used in the production of yarn. Yarn quality prediction models can be used to optimize the spinning process. Prediction and simulation are carried through the use of various modelling tools ranging from regression to Artificial intelligence. Cotton grading, fibre quality index, yarn count, yarn tensile properties, yarn irregularity of ring spinning system and rotor yarn tenacity and rotor yarn hairiness were successfully predicted using AI models and reported to have high accuracy. AI learning methods used are Kohonen neural networks, Back propagation ANN, fuzzy logic, support vector machine, Adaptive neuro fuzzy interface system and hybrid models. Mean absolute error, correlation coefficient and classification accuracy was used by majority of the researchers to assess the neural network model performance. Number of hidden neurons optimized varied from 4 to10.

Keywords: Artificial intelligence, cotton, neural networks, prediction, spinning, yarn

Cotton is the dominant fibre in textile industry for the manufacture of clothing. Cotton cultivation in India has led to the production of 360 lakh bales of cotton and consumption of 269 lakh bales in 2019-2020 (CCI, 2022). India is number one in cotton production and second in consumption next only to China. Cotton spun yarn production in India stands at 4208 mkg (Ministry of Textiles, GOI, 2022) for the year 2018-2019. Major value addition of cotton is done through spinning of yarn and then converting it to fabric through knitting and weaving. Knitted fabric are then converted into mostly inner wear, T shirts and woven fabric are used in the manufacture of outer wear and home textiles. Quality of final garment and home textiles depends on the type of yarn used and its quality. Similarly, Yarn quality depends on the quality of its raw material that is cotton and also the process parameters used in the production of yarn. Even today small sample is processed to predict the yarn quality and then purchase decision is made. If models are available to predict the yarn quality, then this trial process can be eliminated. Yarn quality prediction models can be used to optimize the spinning process. Prediction and simulation are carried through the use of various modelling tools ranging from regression to Artificial intelligence.

Artificial Intelligence (AI) is employed in a wide range of disciplines, including scientific research, education, manufacturing, logistics, transportation, defence, law enforcement, advertising, and art. Many countries are investing on AI as futuristic technology. Start-ups in AI has got a funding of USD 38 billion in USA and USD 8 billion in Europe. Govt. in China has setup high level commission to study AI. AI has a potential to contribute 10 per cent of India's GDP by 2025 amounting to $500 billion (NASSCOM, 2022). AI has a capacity to learn, evolve and transform all fields. In the medical field, a trained deep neural network predicted antibiotic activity in molecules that are structurally different from known antibiotics. Strokes *et al.,* (2020) trained a deep neural network and performed predictions on multiple chemical libraries and discovered a molecule from the drug named as halicin. AI model has identified eight antibacterial compounds that are structurally distant from known antibiotics. Similarly, AI has been used for modelling various manufacturing activities of textile engineering ranging from cotton classification to garment manufacturing. This paper reviews the AI research work carried out in cotton processing area.

ARTIFICIAL INTELLIGENCE

Technologies, particularly general-purpose technologies, have been the economic drivers for the last three centuries. Three technologies that contributed to the growth are the steam engine, internal combustion engine and electricity. In the present age, one technology that has potential to contribute economic growth is AI. John McCarthy introduced the word Artificial Intelligence in 1955 (Brynjolfsson and Mcafee, 2021). Today, Artificial intelligence is a field in computer in science. Artificial Intelligence is the science of making intelligent machines, especially intelligent computer programs (MOCI, GOI, 2022). List of areas where AI is commonly used are: computer vision, speech recognition, natural language processing, computational logic and neural networks. Researchers mimicked human brain (biological neural network) and developed model that is capable of learning from examples. Modelling algorithm that are used to learn from examples are called as Artificial Neural Network (ANN). Machine learning is another term used for ANN (Fig 1).

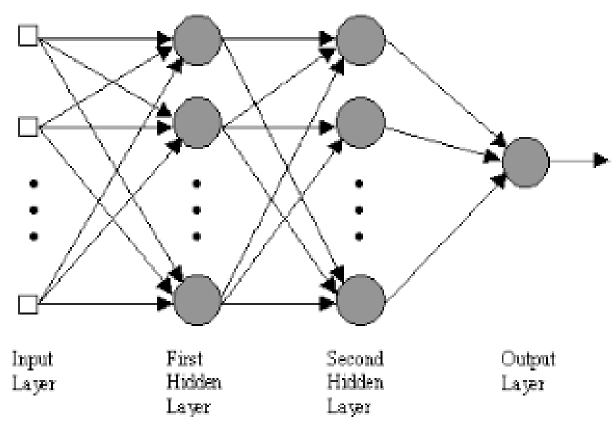

Fig 1 Artificial Neural Network

MACHINE LEARNING

Among AI, machine learning is the key technology. Software development so far was done by codifying the knowledge and procedures and embedding in machines. Coder has to understand the knowledge and convert it to codes that computer can understand. This is not only tedious process but also not possible to code if the knowledge is tacit. For example coding for speech recognition or image recognition is difficult to express in computer codes. Today, machine learning is able to pick up knowledge from examples and it is able to code implicit knowledge.

AI application in speech recognition has resulted in reduction of error rate form 8.5 per cent to 4.9 per cent (Brynjolfsson and Mcafee, 2021). Machine learning comprises prediction and pattern recognition. Machine learning is replacing older algorithms and offers improved performance. Currently, major research is going on in machine learning. Deep learning is one of the method in machine learning. Compared to other methods of machine learning, deep learning uses several layers of neurons between input and outputs. Image recognition accuracy is improving such way that in coming years it may replace ID cards in corporate world and remove drivers in auto cars.

METHODS OF MACHINE LEARNING

Most widely used method in machine learning is supervised learning. In this method, machine is supplied with a set of inputs and out puts as an example. Machine after learning from examples, it will predict the output if an unknown is fed to the machine. For example, if a picture of plant is shown to a machine learned model, it will tell the name of the plant. If we are able to expose the machine with complete set of input and output combinations, then the machine prediction accuracy will improve multifold and even go to the level of 100 per cent accuracy. With the advent of super computers, one can process large data in a short span of time. This speed allowed AI researchers to develop a new learning method called deep learning. In deep learning millions of data sets are processed through machine and it is able to codify the entire complex relationship involved between input and output. Amazon is using memory based filtering algorithms for making recommendations to customers.

Another method of machine learning called unsupervised learning is yet to gain momentum. Unsupervised learning method involves finding pattern in a data. In this learning method, only inputs will be given, machine has to find patterns and group data with meanings. This is most difficult task. Researchers are yet to come out with a machine learning method that is able to give meaning to the classified patterns.

Reinforcement learning is another learning approach in machine learning. This approach is successfully used to optimize data centre power usage and to develop trading strategies for the stock market. In reinforcement learning systems, one has to specify the current state of the system, list of allowable action, constraints in allowable actions and goal. The system will find out the best way to reach the goal using allowable actions. Microsoft used reinforcement learning to select headlines for its website news by “rewarding” the system whenever the visitors clicked on the link. Even though various types of machine learning methods are available, the widely used learning method in various industries are supervised learning. Textile industry is no exception to that and most of the studies reported are belong to supervised learning method.

YARN COUNT PREDICTION

Quality specification of yarn starts with yarn count. Yarn count produced depends on the end use and subsequent process used. Home textile needs coarse count whereas apparel needs fine count. Raw cotton quality is judged by the fact that what count the cotton will be spun. Raw cotton suitable for fine count can be spun to coarse count without any issue. However the reverse is not possible. That is spinning of fine count from high micronaire and low fibre length cotton is difficult. Prediction of yarn count that could be spun from given cotton is useful information for spinner to plan for its end use. Visalakshi *et al.*, (2022) developed a model based on fuzzy inference theory for the prediction of yarn count from HVI fibre properties and did not go did not go beyond yarn count prediction.

HIGHEST SPINNABLE COUNT INDEX

Cotton is spun to particular yarn count based on the quality parameters of cotton. Finer and higher yarn count requires high fibre length, low micronaire with high maturity, high uniformity ratio, low trash content and high fibre strength. Cotton unlike manmade fibre, it is not possible to engineer the fibre specifications depending on the requirements of spinners. Cotton spinning involves sequence of processes. Good quality cotton is required to improve the performance of spinning. Since multiple parameters of cotton and its spinning performance decides the quality of spun yarn, it is not possible to set the machines parameters straight at first go. So, spinner normally process small quantity of cotton to predict it's spinning performance, so that bulk processing can be done smoothly. In case of research institutions, fibre quality evaluation and spinning performance study is carried out to select suitable variety for commercial cultivation. The process adopted in research institutions for evaluation of spinning quality differs from country to country. For example in USA, all cottons are spun to two known counts depending on the staple category, viz., short staple is spun to 8s and 22s, medium staple and long staple to 22s and 50s and extra-long staple to 50s and 80s. The processing technique adopted is dependent on the group to which the cotton belongs. The average CSP for two counts is reported. Where as in Egypt, all cottons are spun to single count and their yarn CSP is used to rank the cotton. However both the approaches are not suitable for Indian cottons. The range of varieties of cotton produced and counts spun in India required a different approach. One of the problems with the single count approach is that some of the cottons may not be spinnable to that particular count. Moreover, it is certainly doubtful, whether this method would distinguish between two cottons at the other end of the spinning value scale, *i.e.* if cotton A is slightly better in lea strength at 20s count, it is by no means certain that cotton A would also be better than cotton B in other yarn counts.

In Central Institute for Research on Cotton Technology (CIRCOT), spinning is carried out using normal processing methods adopted in spinning mills. In this test two counts are spun, one under spun and the other over spun as decided by CIRCOT CSP norms. The two counts with its CSP are reported. Here again the comparison between two cottons is difficult, if they are spun to different sets of counts. Understanding this problem, an integrated index called Highest Standard Count (HSC) was developed.

HSC is the finest count of yarn that can be spun economically with a standard medium twist and has a certain standard lea CSP. The counts that are spun higher than HSC will have less CSP and counts that are spun lower than HSC will have more CSP than the standard as shown in Fig 2. Thus the HSC of cotton is a single integrated index, which provides an easy way for comparing the quality of cottons. Measurement of HSC involves the spinning of under and over spun counts using a full spinning test and calculating HSC from their CSP values. This is time consuming, labour and machine intensive process.

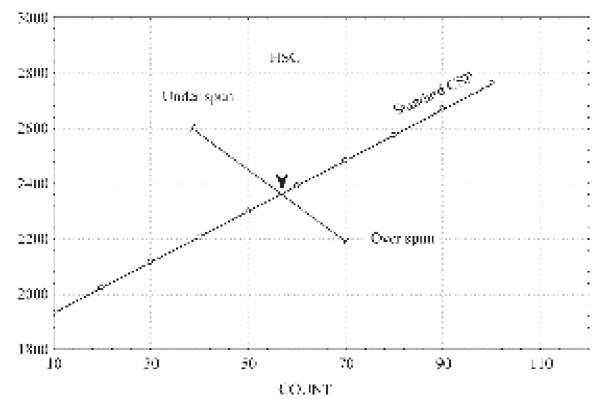

Fig 2 Highest Spinnable Count

Artificial neural network (ANN) model was developed for predicting highest standard count (HSC) from fibre properties, namely 2.5 per cent span length, uniformity ratio, micronaire and bundle strength(Shanmugam and Doke, 2005). The developed ANN model was compared with the mulltiple regression and fibre quality index (FQI) based regression models. ANN ranking of fibre properties was carried out using difference in test performance values as indicator and in case of multiple regression, standardized regression coefficients were used. It was observed that in both ANN and multiple regression models, the ranks of span length and bundle strength are the same. The span length is the largest contributor for HSC and the bundle strength is the least contributor. The mean absolute errors of ANN and multiple regression equation are found to be less by 15 per cent and 11 per cent respectively in comparison with FQI-based linear regression equation.

RING YARN TENSILE PROPERTIES

The term yarn quality refers to various properties of yarn starting from yarn strength, elongation, hairiness, evenness and imperfections. Researchers used mathematical, statistical and artificial intelligence based models to predict yarn properties. Among these approaches, AI based modelling gained increased importance among researchers. Yarn tensile properties determine the fabric tensile properties. Yarns that are having high strength perform better in weaving and processing machinery. Single yarn breaking strength, breaking elongation and Yarn CSP (count strength product) are normally referred as tensile properties

Cheng and Adams (Cheng and Adams, 1995) one of the earliest authors worked in ANN used upper half mean length, length uniformity, short fiber content, strength, fineness, maturity ratio, reflectance and yellowness and predicted 22s ring spun yarn CSP. Micronaire was not used in their study. Model with four hidden neurons found to be the best for yarn strength prediction with a Correlation coefficient of 0.850.

Mechanist model was compared with a statistical model (regression equation) and a neural network based model for yarn tenacity of cotton yams (Guha *et al.*, 2001). A feedforward neural network was created using seven units in the input layer for fibre fineness, yam count, yam twist, breaking stress of fibre, breaking strain of fibre, mean length of fibre and CV of break force, one hidden layer and one unit in the output layer for yam tenacity. Neural networks gave an average error of 6.9 per cent as against 9.3 per cent for the mechanistic model and 9.9 per cent for the statistical model for predicting yarn tenacity. This study conclusively proved the superiority of neural network models over mechanistic models and simple regression equations for predicting ring-spun yam tenacity. In another research work, Yarn strength was predicted from cotton fibre properties using ANN and compared with Solovev's model for prediction accuracy (Ahmad, 2016). Slovev's model predicted the strength of yarn in gf/tex from fibre strength, linear density of yarn, linear density of fibre, fibre length and correction factor for quality of process and yarn twist. Similar to Slovev's model, in this study also yarn count, yarn twist, fibre length, fineness, maturity and tenacity were selected as input variables to ANN and output as yarn strength. The yarn counts ranged from 6.96 – 24.06 Ne with twists ranged between 338 – 921 twist per metre. The mean error in prediction of yarn tenacity of ANN method is 4.17 per cent, compared to 19.81 per cent of Solovev's model.

A back-propagation artificial neural network was used to develop a model relating to cotton fibre properties and micro-spun yarn lea CSP (Shanmugam *et al.*, 2001). Fibre properties such as span length, bundle strength, fineness, breaking elongation, uniformity ratio and percentage of mature fibres was studied. Neural network architecture having five hidden neurons in one hidden layer and an epoch size of 12 gave better prediction. The mean absolute error of neural network model was found to be 60 per cent lower than those of the regression models.

El-Geiheini *et al.,* (2020) modelled yarn tensile properties using AI. Work was carried out to employ image processing and artificial neural networks for modeling yarn tenacity and elongation per cent. Yarn samples were wound around a blackboard using the appearance tester. Sample images were captured and used as vector network inputs and output was yarn tenacity and elongation. Cotton yarn tenacity and elongation of yarn count 24, 30 and 50s Ne training errors (MAE) were found to be 0.120 and 0.074 for yarn tenacity (RKM) and elongation% respectively. Instead of predicting yarn tenacity from appearance board images, if prediction was done for yarn grade, that would have been more useful.

YARN IRREGULARITY

Yarn irregularity is important as it affects the fabric appearance and strength. Yarn irregularity is interchangeably used with other terms namely evenness, unevenness, levelness and regularity. Yarn irregularity refers to yarn mass per unit length (linear density) variation measured using evenness tester that usually works on the capacitance principle. Zellweger Uster Irregularity tester is a popular instrument in evaluating of yarn samples. In this instrument, a yarn sample length of 1 cm mass was measured using capacitance and the variation of mass was expressed using CV (%). Raw cotton properties and machine settings, process parameters contribute to yarn irregularity. Knowing the effect of cotton parameters on yarn irregularity will help in procuring right type of cotton. In this context, Upper Quartile Length, mean fiber length, percent short fibers, neps and total trash was measured using Advanced Fibre Information Systems (AFIS) and were used in the neural network prediction model of yarn irregularity in the count range of 16-30 Ne (Zhu and Ethridge, 1996). Correlation coefficient between the experimental yam irregularity CV (%) and the prediction yarn irregularity CV (%) was from 0.7984-0.8808 for five different neural networks. Among the studied neural networks, it was found that one layer with 10 hidden neurons gave high correlation coefficient.

ROTOR YARN QUALITY

Two spinning systems that are popular in cotton industry are ring spinning and rotor spinning. Similar to ring spinning, cotton quality plays a key role in deciding the yarn quality. Rotor spinning is very sensitive dust and fine trash particles. Rotor spinning runs at a delivery speed of 300 m/min and capable of making yarn in the count range of 6s Ne to 40s Ne. However compared to ring spun yarns rotor yarns are low in strength. Fabric mechanical comfort for rotor yarn fabrics was poor due to presence of wrapper fibres in the yarn structure. Rotor spinning requires fine fibres for a trouble free spinning. A minimum of 100 fibres is needed in the yarn cross-section for rotor spinning. Rotor yarn properties are affected by rotor groove shape (angle, radius, depth), rotor diameter, rotor speed, doffing tube (navel) and cotton fibre properties.

Fibre bundle tenacity, elongation, upper half mean length (UHML), uniformity index, micronaire, reflectance degree and yellowness and yarn count (15 to 30 Ne Ring, 10 to 30 Ne rotor) were used as inputs and predicted yarn tenacity of rotor and ring yarns using neuro fuzzy and ANN models (Majumdar *et al.*, 2005). The mean error of prediction for both the neuro-fuzzy and ANN models is less than 5 per cent for ring yarns and less than 2 per cent for rotor yarns. The predictive power of the neuro-fuzzy system is better than that of the linear regression model and comparable with the ANN.

Hairiness refers to those fibers located outside of the yarn body and is considered as an undesired factor. Minimizing yarn hairiness of cotton rotor-spun yarns is important as yarn hairiness affects weaving efficiency. Prediction of hairiness based from cotton parameters and rotor spinning machine variables has always been interest for researchers. The artificial intelligence models such as adaptive neuro fuzzy interface system (ANFIS) and support vector machine (SVM) present high potential tools to be used in nonlinear and complicated engineering problems such as predicting properties of textile yarns.

Vadood *et al.*, (2018) predicted the hairiness of cotton rotor yarns by Artificial Intelligence using adaptive neuro fuzzy interface system (ANFIS) and support vector machine (SVM). Yarn hairiness was tested using Shirley hairiness tester and number of hairs that are protruding from yarn that are having length more than 1mm were measured. Hairs/m rotor yarns studied were found to be in the range of 18 to 30. Machine parameters namely rotor type, rotor diameter, doffing-tube nozzle and torque-stop were used as input variables and output variable was yarn hairiness. The results showed that the accuracies of SVM, ANFIS and ANN models are almost the same with MAPE of 3.9.

HYRBID NEURAL NETWORKS

Hybrid neural network is a network with a combination of different artificial neural networks and approaches. It utilizes features of varying neural networks and approaches to achieve optimum results. Hybrid models (ANN+ANN) and ANN+FUZZY logic was used to map fibre and yarn properties (Ghanmi *et al.*, 2021). Count range 7s Ne to 21s Ne, TPI range - 11 to 2 and cotton of five varieties were studied. Four HVI characteristics namely fibre length, micronaire, elongation and strength and process parameters particularly count and twist were used as input to neural network. Yarn quality index deduced from tenacity, elongation, CVm and hairiness used as output. Yarn quality index was created by equating yarn properties values to uster percentiles. It was found that ANN+ANN performance (MAE - 0.03, Mean relative % error - 6%) was superior to ANN+FUZZY logic (MAE -0.04, MRPE - 9.1%) in predicting yarn quality index.

Doran and Sahin (2020) predicted the quality characteristics of cotton/elastane core yarn using artificial neural networks and support vector machines. According to their findings, prediction of yarn CVm, hairiness, breaking force, elongation and tenacity was successful by the models trained with principal component analysis reduced inputs of HVI and AFIS fibre properties. Both SVM model and ANN models gave accurate predictions for the Coefficient of Variance of mass (CVm), hairiness and Reisskilometer quality characteristics of the cotton/elastane core yarn at an accuracy of 91per cent, 93 per cent and 95 per cent respectively.

CLASSIFICATION AND GRADING

Grading refers to measuring or judging the quality and assigning value or name to it. Product's quality is indicated by grade. One can determine the quality of a product by looking at its grade. Cotton grading is done using fibre testing instruments as well as using manual grades. In manual grading, cotton graders visually compare the specimen cotton with standard bench mark cotton boxes and assign names viz: Extra super fine, super fine, fully good and good. Manual grading being subjective and tend to vary between graders, research was done to replace manual grading with AI based grading. Shanmugam *et al.*, (2002) developed an artificial neural network model by linking instrumentally evaluated cotton quality parameters and manual cotton grades. Fibre properties such as 2.5 per cent span length, micronaire, bundle strength, uniformity ratio and percentage of mature fibres was used as inputs to ANN model and EICA cotton manual grades were used as output. This study demonstrated that artificial neural network can be effectively used to predict the manual cotton grades from fibre properties. The classification rate obtained from the ANN model ranged from 33 to 100%, with an overall classification rate of 67 per cent. The overall classification obtained from the model is good and the predictions remained in the close vicinity of actual grade.

Cotton is classified into five staple length groups as short, medium, medium long, long and extra long. These groups are made purely on the staple length values. However equally important other fibre parameters like strength, fineness, maturity and uniformity ratio are not considered in the staple length group. Other than staple length, remaining fibre parameters are given rating for the entire spectrum of cotton fibre. This is not serving the intended purpose as spinning potential not only depends on the staple length groups but also on other properties like micronaire. Hence there is a need to reclassify all the cotton fibre parameters in to specific groups for all the properties. As the existing classification is arbitrary an attempt was made to use pattern recognition capability of AI. Kohonen neural networks (Fig 3) was used to obtain classification for fibre parameters namely span length, micronaire, bundle strength, uniformity ratio and % of mature fibres (Shanmugam *et al.*, 2003) . Kohonen neural networks classified cotton data into four meaningful groups. Dependency analysis revealed that the span length was negatively correlated with maturity, micronaire and uniformity ratio. Kohonen neural network analysis has further revealed the presence of two clear grouping within the medium staple category based on the fineness of fibre. This type of grouping with range of values to all the parameters for each group, helps to identify the spinning potential of a cotton more exactly. Except fibre elongation, the other properties have distinct range of values for each group. The developed model is found to classify cottons accurately (Shanmugam and Doke, 2006).

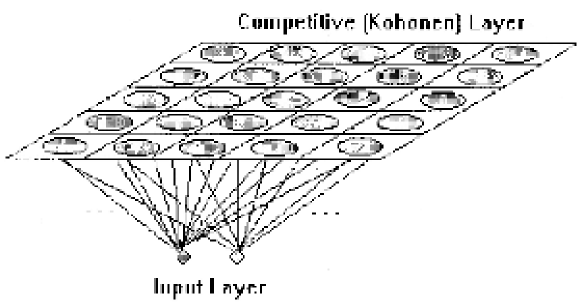

Fig 3 Kohonen neural networks

CONCLUSION

Cotton grading, fibre quality index, yarn count, yarn tensile properties, yarn irregularity of ring spinning system and rotor yarn tenacity and rotor yarn hairiness were successfully predicted using AI models and reported to have high accuracy. AI learning methods used are Kohonen neural networks, Back propagation ANN, fuzzy logic, support vector machine, Adaptive neuro fuzzy interface system and hybrid models. Mean absolute error, correlation coefficient and classification accuracy was used by majority of the researchers to assess the neural network model performance. Number of hidden neurons optimized varied from 4 to 10. The final developed model of the researchers are not available in the public domain and hence it is not possible to build up on the already existing models. Google autoMl is a platform that allows one to use pre-existing neural network models to fine tune the new models. Instead of building new model from scratch, one can use existing model. This approach is called as transfer learning and it will help to use minimal data seat in AI modelling. It is anticipated that in future, textile researchers in AI modelling will deploy their models in public domain so that other stake holders can use the existing models. This will also help in build future models in cotton processing with minimal data.

Artificial intelligence has been applied in various areas of yarn spinning processes. Testing of cotton in HVI or AFIS gives huge number of test parameters. Spinning technician are unable to use all the parameters and they use only selected parameters to buy cotton and to set machine process parameters. AI enabled models in future will be able to use all the parameters and will be able to predict quality of output of machine accurately. This will reduce trial and error methods adopted today's scenario. Cotton processing is mostly carried out with the experienced staff and once they leave the industry their knowledge also lost. Expert systems which were used earlier to capture the knowledge has been phased out due to the difficulties in capturing knowledge from experts and coding that knowledge. AI is able to capture knowledge through modelling and hence it will be used in coming years extensively in cotton processing. Implementation of AI tools and models will enhance the efficiency of cotton processing industry.

REFERENCES

Ahmad, G.G. 2016. Using artificial neural networks with graphical user interface to predict the strength of carded cotton yarns. *J Text Inst*, **107:** 386–94.

Brynjolfsson, E. and Mcafee, A. 2021. The business of artificial intelligence. *Harv Bus Rev Spec Issue*, Winter 2021: 20–29.

CCI., 2022. cotton Balance sheet. (https://cotcorp.org.in/current_cotton.aspx accessed on 13 April 2022).

Cheng, L. and Adams, D.L. 1995. Yarn Strength Prediction Using Neural Networks: Part I: Fiber Properties and Yarn Strength Relationship. *Text Res. J*, **65:** 495–500.

Doran, E.C. and Sahin, C. 2020. The prediction of quality characteristics of cotton/elastane core yarn using artificial neural networks and support vector machines. *Text Res J*, **90:** 1558–80.

El-Geiheini A., ElKateb, S. and Abd-Elhamied, M.R. 2020. Yarn tensile properties modeling using artificial intelligence. *Alex Eng J*, **59:** 4435–40.

Ghanmi, H., Ghith, A. and Benameur, T. 2021. Ring spun yarn quality prediction using hybrid neural networks. *J Text Inst*, 1-9 https://doi.org/10.1080/00405000.2021.2022826.

Guha A., Chattopadhyay, R., and Jayadeva. 2001. Predicting Yarn Tenacity: A Comparison of Mechanistic, Statistical, and Neural Network Models. *J Text Inst*, **92:** 139–45.

Majumdar, A., Majumdar, P.K. and Sarkar, B. 2005. Application of an adaptive neuro-fuzzy system for the prediction of cotton yarn strength from HVI fibre properties. *J Text Inst*, **96:** 55–60.

Ministry of Textiles, GOI., 2022. Production of major textile items.pdf. (http://texmin.nic.in/sites/default/files/Production%20of%20major%20textile%20items.pdf accessed on 29 January 2022).

MOCI, GOI., 2022. Report of Task Force on Artificial Intelligence | Department for Promotion of Industry and Internal Trade | MoCI | GoI. (https://dpiit.gov.in/whats-new/report-task-force-artificial-intelligence accessed on 25 April 2022).

NASSCOM., 2022. AI-as-a-Service: Democratizing AI For Scale. (https://nasscom.in/knowledge-center/publications/ai-service-democratizing-ai-scale accessed on 13 April 2022).

Shanmugam, N., Chattopadhyay, S., Vivekanandan, M. and Sreenivasamurthy, H. 2001. Prediction of micro-spun yarn lea CSP using artificial neural networks. *Indian J Fibre Text Res*, **26:** 372–77.

Shanmugam, N. and Doke, S. 2006. Classifying fibre attributes of cotton using Kohonen neural networks. *Indian J Fibre Text Res*, **31:** 583–87.

Shanmugam, N. and Doke, S. 2005. Highest standard count estimation from fibre parameters using neural network techniques. *Indian J Fibre Text Res*, **30:** 302–08.

Shanmugam, N., Vivekanadan, M.V. and Sreenivasan, S. 2002. Objective cotton grading: An artificial neural network. *Indian Text J*, **112:** 21–26.

Shanmugam, N., Vivekanandan, M. and Doke, S. 2003. Pattern recognition in cotton data using Kohonen neural networks. *Ind. Text J*, **113:** 21–25.

Stokes, J.M., Yang, K., Swanson, K., Jin, W., Cubillos-Ruiz, A. and Donghia, N.M. 2020. A Deep Learning Approach to Antibiotic Discovery. *Cell*, **180:** 688-702.e13.

Vadood, M., Ghorbani, V. and Safar Johari M. 2018. Predicting the Hairiness of Cotton Rotor Spinning Yarns by Artificial Intelligence. *J Text Polym*, **6:** 15–21.

Visalakshi V., Yogalakshmi, T. and Castillo, O. 2022. Analysis of Cotton Yarn Count by Fuzzy Logic Model. *In Proceedings of International Conference on Computational Intelligence* (R. Tiwari, A. Mishra, N. Yadav, & M. Pavone, eds). Springer Singapore, Singapore, 349–61.

Zhu, R. and Ethridge, M.D. 1996. The Prediction of Cotton Yarn Irregularity Based on the 'AFIS' Measurement. *J Text Inst*, **87:** 509–12.

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