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An ML-Based Approach for Optimizing the Productivity and Efficiency of the Apparel Industry by Focusing on Trainee Employees

[1]Rathnayake R.A.S.T, [2]Munmulla D.N, [3]Samadhi Rathnayake, [4]Peiris M.I.M, [5]E.A. Asini Bovindya, [6]Anuradha Karunasena

[1,2,3,4,5,6]Department of Information Technology, Sri Lanka Institute of Information Technology, Malabe, Sri Lanka
Authors E-mail: [1]it20043964@my.sliit.lk, [2]it20212186@my.sliit.lk, [3]samadhi.r@sliit.lk, [4]it20165352@my.sliit.lk, [5]it20141974@my.sliit.lk, [6]anuradha.k@sliit.lk

***Abstract* - In the apparel industry, training is crucial because it brings skilled workers and promotes increased productivity. However, typical manual approaches frequently fail to accelerate the training process, resulting in unsatisfactory results properly. In this paper, the authors describe an innovative strategy to increase the productivity and efficiency of sewing machine operator training processes by using a machine learning-driven web-based application. The proposed application leverages the power of machine learning models to identify and solve crucial areas for improvement. It specifically detects wrong hand movements, incorrect trainee sitting postures, defects in sewed garments, and errors in dexterity tests during the training period of the sewing operators. Notably, the Graphical Neural Network (GNN) model detects erroneous hand movements with an astonishing 85% accuracy. The Convolutional Neural Network (CNN) model excels in detecting incorrect sitting postures, with an impressive 75% accuracy. Furthermore, the CNN model detects garment defects with an accuracy of 95%, while the CNN model detects test result errors in dexterity tests with an astounding 97% test accuracy. By using the proposed web tool for screening, the authors expect to see a significant increase in trainee productivity and efficiency. Lastly, the machine learning-driven web-based application is a great tool for optimizing the garment industry's training process. Future plans include increasing the application's functionality, introducing new features, and investigating its applicability across multiple sectors within garment manufacturing. By adopting this unique approach, the apparel sector can achieve significant gains in training outcomes, resulting in a more skilled and efficient workforce.**

Keywords: Convolutional Neural Network (CNN), Graph Neural Network (GNN), Recurrent Convolutional Neural Network (RCNN), Garment Sewing Data (GSD), Employee training.

I. INTRODUCTION

In Sri Lanka, the apparel industry plays a vital role in the country's economy, contributing over 52% of total export earnings. The industry's primary objectives revolve around producing high-quality finished garment products within specified timeframes. Ensuring efficient production and meeting target deadlines are key focal points for this sector.

In any industry, Employees are regarded as rare, non-imitable, and valuable resources for a firm, and their performance ultimately determines the success or failure of the business. The labor productivity of employees directly affects the success of any organization. In the apparel industry, labor productivity directly impacts business performance, influencing the quality of garments and the timely delivery of products. As seen in [1], improving labor productivity can lead to enhanced business outcomes and customer satisfaction in the apparel industry.

The training process in the apparel manufacturing industry plays a very important role in equipping new sewing operators with the necessary skills and knowledge to meet the demands of the fast-paced production environment. Specialized training programs led by industry experts enhance workforce skills, leading to increased labor productivity. Investing in continuous learning cultivates a proficient workforce, contributing to overall organizational success. The empirical study confirmed that the training process positively impacts operational-level employee performance in the selected apparel organization in Sri Lanka [2]. Investing in employee training proves to be a valuable strategy for improving overall organizational effectiveness.

In order to address the inefficiencies and limitations of the traditional methods employed in training centers, this research paper presents a comprehensive solution to enhance training efficiency and productivity in the apparel manufacturing industry. The authors have introduced

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automated methods for the ongoing manual process in the industry including the identification of imprecise hand movements, garment defects and errors in hand dexterity tests, and trainee sitting posture maintenance by leveraging computer vision, video processing, and machine learning.

II. LITERATURE SURVEY

Previous research has been conducted in recent years to detect the movements of humans. Prior investigations predominantly relied on image-processing models [3], but these methods struggled to capture the intricate nuances of the stitching processes and specific movements. The research builds upon the foundational work laid out in previous studies [4] and [5], which underscored the potential of video processing technology to enhance outcomes while reducing time complexity. Notably, this approach represents a departure from prior methods by eliminating the need for Support Vector Machines (SVM).

The relationship between dexterity test outcomes and sewing machine operator performance has been explored in the earlier study. The goal of a study undertaken by Indika Priyantha Kaluarachchige in May 2020 [6] was to determine how dexterity affects sewing machine operators' abilities at work. The selected clothing manufacturer now uses four dexterity tests for sampling: marble, pinboard, card, and puzzle. Eighty-eight sewing machine operators from garment companies in the Katunayake Industrial Processing Zone were involved in the study, which used a random sample methodology. The factory management information system was used to collect performance information, such as efficiency and defect percentage.

The sewing machine operators' performance was positively impacted by their mastery of the marble, cards, and puzzle activities, according to correlation analysis and hypothesis testing. Notably, their capacity for puzzle-solving had the greatest influence. Examining the data from this study makes it clear that there is a connection between sewing machine operators' output and the results of their dexterity tests. Using this information as a foundation, this study attempts to monitor and score the dexterity test by using machine learning and image processing techniques. Dexterity assessments are important in assessing sewing machine operator performance, according to the research. In order to improve training procedures in the apparel business, the researchers want to better understand how dexterity test results relate to certain hand functioning skills through this research.

In their study, Kaicheng Yin and Weidong Yu [7] introduced a garment product defects detection system specifically designed for the apparel industry. The researchers employed image processing principles to identify only two types of garment defects including defects on the seams and defects on the cloth surface. The researchers extracted features such as average value, standard deviation, and smoothness from defect images, and utilized these features in a neural network-based classification approach to accurately identify and classify garment defects. However, the defects they identified were not according to a relevant sewing machine.

In study 2021, a team of researchers from China [8] proposed an algorithm for accurately calculating the weft inclination angle of textile fabrics. By employing the machine vision platform and the developed algorithm, the researchers provided a solution for real-time monitoring and control of the weft inclination angle in textile cloth production.

In 2022, researchers Guangchi Liu, FuWei Wang, and HanShuo Hui [9] conducted a research study on industrial filter cloths. The study collaborated with Tian Cheng Environmental Protection Company to obtain data through an academic research agreement and utilized the Mask R-CNN convolutional neural network model for only the classification and identification of filter cloth defects.

In 2019, Jacintha and S. Karthikeyan [10] from India proposed a new structural method for identifying flaws in the fabric. The technique uses the similarity of each pixel (Himage), which is a new feature extraction technique, to identify flaws in fabric samples. According to [11], a hybrid model that combines genetic algorithms and neural networks to classify garment defects was introduced in China. The model was specifically designed to classify garment defects into three types including seams without sewing defects, seams with puckering defects caused by stitching faults, and seams with pleated defects. However, the defects were not classified according to a relevant sewing machine. The aim of their research was to increase the accuracy of defect identification in the process of garment manufacturing.

Effective posture classification, crucial for the goals of the apparel industry, relies on intricate signal processing and machine learning algorithms due to complexities in analyzing textile sensor pressure data. Yet, textile pressure sensors face challenges in sensing precision and environmental influences, potentially affecting accurate posture assessment. For more details, see [12]. According to [13] Wen-June Wang's posture recognition method boasts 99% accuracy, leveraging Kinect's depth data and efficient LVQ neural network for cost-effective and shadow-resistant results. Occlusions pose recognition challenges.

CNN-based methods extract video frame features, excelling in action recognition and object detection due to spatial hierarchies. Combining pressure sensors and images enhances posture classification. Proper posture aids

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musculoskeletal health, preventing strain and disorders for better overall well-being [14].

By merging pressure sensors with image concepts, a holistic video processing strategy emerges, bolstering posture and activity identification. Synergizing these methods enhances system accuracy, benefiting healthcare, sports analysis, and human-computer interaction domains. Pressure sensors, such as textile pressure sensors, offer a unique perspective by capturing pressure distribution and variations on surfaces. These sensors provide valuable information for the study focused on identifying standing postures via an intelligent floor with pressure sensors. CNN was applied forrecognition, using pressure data transformed into images. Enhanced CNN architecture improved accuracy, showcasing potential in smart manufacturing's posture recognition[15]. In proposed system detects the sitting postures of sewing operators using video technology.

III. METHODOLOGY

The "Sew Smart" web-based solution automates the manual processes existing in the training centers of the apparel industry including detecting imprecise hand movements, detecting garment defects, and automating the process of detecting errors in hand dexterity tests and monitoring of trainee sitting postures.

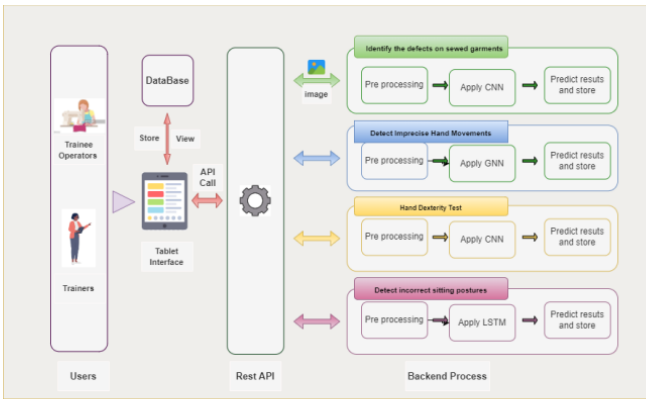

Figure 1: System Overview Diagram

A) Detect Imprecise Hand Movements

The implementation of the method includes several critical stages. Initially, video recordings are collected, capturing sewing operators as they perform various sewing tasks, particularly focusing on actions such as placing garment pieces on the sewing table. This video dataset serves as the base training data, presenting various opportunities for analysis.

Then, advanced computer vision techniques are used to meticulously extract hand movements from the collected video footage. By using complex algorithms, accurate detection and tracking of hand regions in video frames corresponding to sewing operators' hands is achieved. This complex process facilitates a detailed analysis of the hand movements inherent in the sewing process. The extracted hand movements are then transformed into a graph structure, in which nodes represent specific hand positions or gestures, and edges encode the temporal interdependencies between these movements. This graph configuration serves as input for the Graph Neural Network (GNN) model. Leveraging its inherent ability to understand temporal dynamics and unravel complex relationships within the graph, the GNN model intelligently discriminates between correct and incorrect hand movements.

An initial dataset consisting of 300 videos depicting sewing operators' hands was used to train and evaluate a GNN model. However, the model faced challenges in precisely identifying sewing operators based on hand movements alone. To improve accuracy, an additional dataset was obtained that included videos of the upper body of sewing operators. By incorporating these complementary videos into the training method, the GNN model exhibited improved performance, highlighting its proficiency in recognizing sewing operators by combining arm and upper body movements. The pool of 300 videos was divided into distinct training and testing subsets, with 80% of the videos reserved for training purposes and the remaining 20% for evaluation. This segmentation strategy ensures extensive model training while also providing an independent data set for rigorous performance evaluation. This parsimonious approach optimizes the model's learning trajectory and facilitates an accurate assessment of its performance on previously unseen data. Incorporating a comparison with established guidelines, the methodology ensures compliance with predefined garment standard data. Detection of any deviations or wrong movements prompts the sewing operators to issue warnings and feedback.

B) Hand Dexterity test

There are three steps to the sewing machine operator training process. They are foundational training, operational training, and advanced machine training. By focusing on the fundamental training stage, this study intends to increase training process efficiency and improve existing processes.

The examination of the dexterity test, a vital evaluation of trainees' manual skills, is central to this process. The main novelty is the use of machine learning techniques to automate the scoring process of this test by identifying possible error patterns in the test result. A large collection of over 1000 photos representing seventeen error pattern classes has been collected to improve an existing process.

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The acquired dataset is used to train the model, and its accuracy and performance are evaluated using a separate evaluation subset.

The model architecture is made up of neural network layers that are optimized for image classification. It is made up of six Convolutional (Conv2D) layers that learn detailed features from input images successively. Six MaxPooling2D layers with a pooling size of (2, 2) supplement these convolutional layers by lowering spatial dimensions and emphasizing key characteristics.

The Flatten layer then effortlessly turns the pooled features into a 1D vector. This vector is processed in two Dense layers: the first with 64 units, which stimulates non-linear interactions, and the second with 17 units, which caters to the classification of 17 different classes.

Furthermore, the convolutional layers use strides of (1, 1), whereas the MaxPooling2D layers use strides of (2, 2), enabling effective spatial reduction. This combination of Convolutional, MaxPooling, flattened, and Dense layers results in a model architecture optimal for image classification accuracy.

The trained model is then incorporated into a web application, which enables monitoring and automatic dexterity test scoring.

Figure 2: Depicts the actual labels, predicted labels, and prediction confidence scores for three test data images

C) Identify the defects on sewed garments

In the garment error detection process, users have to input images of their sewed garments into the application after they have completed the sewing training with a relevant sewing machine during their training period. Users have to input images of ten sewed garments done in one machine and at the end, the application will calculate the defects percentage of sewed garments. Here the garments that are sewn by the flat seam machine were selected to train the model as the initial step of this project. So the garment defects done by the flat-seam machine are calculated by the application. In the end, the learning percentage of the trainee sewing operators is measured as a result of this process.

A CNN model was used with five layers to identify garment defects. It consists of 2D convolutional layers with, Maxpool2D layers, and a "ReLu" activation function in each. The output flattens into 1D using a dense layer that consists of 64 neurons and a dropout layer and it feeds into another dense layer with 12 neurons and a softmax classifier. The final output goes through an "Adam optimizer" and sparse categorical cross-entropy is used as the loss function for better results.

CNN model was trained using 4 garment error types including wavy-seam defect, open defect, up-down defect, and non-defected with 3 parts train, validation, and test. 0.1 of the data set (10% of the whole) was taken as test data, and 0.1 from the remaining data (9% of the whole) as validation. The rest was taken as the train split. Before feeding into the CNN model, a set of preprocessing steps were followed. The images were resized and rescaled before feeding into the CNN model.

In the garment defects detection process, the user needs to input the images of the sewed garments that are finished during the training process regarding the flat-seam sewing machine. Users have to test with the sewed garment pieces and the learning percentage of the trainee sewing operators will be calculated using the count of the defected images predicted by the system. The data related to each candidate will be added to the database after performing the tests.

D) Identify the incorrect sitting postures of trainee operators

The process begins with the collection of a diverse data set comprising videos of sewing operators exhibiting various postures during their sewing task. These videos are then preprocessed to extract relevant features for posture analysis, ensuring consistent data representation. Before capturing the video, users are guided through a posture guide that provides instructions for correct sewing postures. Additionally, camera calibration is performed to optimize accuracy by adjusting camera settings and position. The methodology's core lies in implementing the LSTM algorithm, a type of recurrent neural network. The LSTM model is trained using pre-processed video data, with correct and incorrect postures labeled accordingly. In real-time, the trained LSTM algorithm analyses the temporal sequence of video frames and promptly detects incorrect postures. Users receive immediate warnings through visual cues, audio alerts, or notifications, facilitating timely corrections. The system's performance is evaluated using metrics such as accuracy, precision, and recall, allowing for refinement based on feedback from sewing operators and instructors. Finally, the methodology involves deploying the system in a user-friendly interface, enabling registered users to capture videos, access the posture guide, and receive real-time

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warnings. By implementing this methodology, the proposed solution offers an effective means of training sewing operators and instructors to detect and rectify incorrect postures, thereby promoting ergonomic practices and mitigating musculoskeletal risks within the sewing industry.

IV. RESULTS AND DISCUSSIONS

A) Detect Imprecise Hand Movements

The system accurately identifies incorrect hand movements based on garment standards data by combining computer vision techniques and a Graph Neural Network (GNN) model. The GNN's incorporation enables it to comprehend temporal dependencies and intricate relationships in hand movements, offering precise operator feedback. Initial training with 300 videos achieved 85.7% accuracy, with ongoing improvements expected to enhance its effectiveness in the industry, guiding operators and boosting overall performance. Graph Neural Networks (GNNs) were chosen for their advantages in making predictions at node and graph levels. They capture essential node information and summarize data for predictions and tasks across the graph. GNNs' transferability is highlighted, enabling the seamless application of new graphs or tasks with similar structures. This adaptability proves valuable when the graph structure is consistent but node features vary. A machine learning model was developed using the Graph Convolutional Network (GCN) architecture. The input data, sized [93, 3, 10], consists of 93 samples, each with 3 features of length 10. The model comprises three GCN layers: conv1, conv2, and conv3. Conv1 takes a 30-size input, producing a 64-size output; conv2 and conv3 work similarly with a 64-size input and output. These layers extract pertinent features. The model includes a linear layer (lin) that maps GCN output to 2 dimensions via linear transformation. Trained for 100 epochs, the model achieved a training accuracy of 0.8529 and a test accuracy of 0.8571, demonstrating proficient label prediction. The training loss at this epoch is 0.3644, indicating label prediction accuracy during training. This GCN model exhibits promise in analyzing graph-structured data for predictions, with the potential for further optimization to enhance generalization on unseen data.

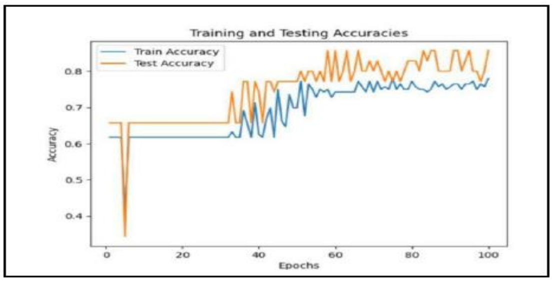

Figure 3: Training and validation accuracy of GCN model

B) Hand Dexterity test

For model training, the study used a dataset of 1000 images. Convolutional Neural Networks (CNN) were popular due to their capacity to translate multidimensional picture data to one-dimensional output variables. CNNs are well known for their precision in image classification and recognition. The CNN obtained an outstanding accuracy of over 97% for test input data throughout the model training phase.

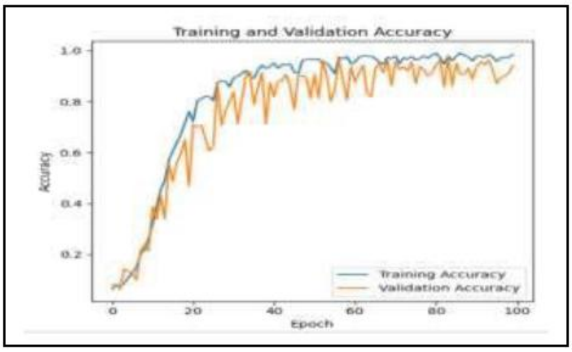

Figure 4: Training and validation accuracy of CNN model

C) Identify the defects on sewed garments

More than 300 images were collected for each garment defect type from the source company, MAS Linea Aqua. CNN has been used as it utilizes multiple layers to learn and detect various features in input images, effectively reducing their high dimensionality while preserving important information. In the model training process, the CNN model obtained over 95% accuracy for the test input data and Fig. 5 shows the training and validation accuracy against 50 epochs of the model.

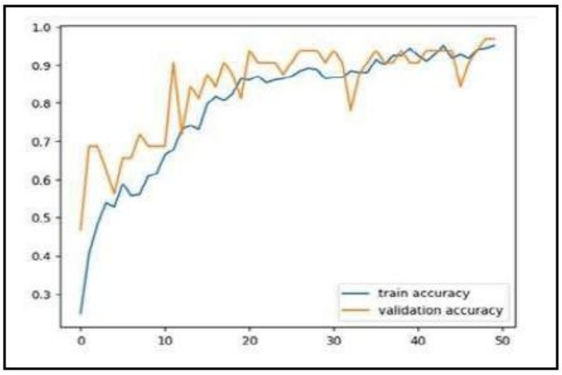

Figure 5: Training and validation accuracy of CNN model

D) Identify the incorrect sitting postures of trainee operators

After exploring various model architectures, the LSTM approach emerged as the most effective choice. This architecture includes multiple LSTM layers and memory cells,

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which contribute to its strong performance in recognizing different body postures. By excelling at capturing changes over time, the LSTM model facilitates accurate posture recognition, even in complex scenarios. The dataset has a Collection of more than 100 videos. Video decomposition into individual frames. Fig. 6 shows the training and validation accuracy against 30 epochs of the model. The CNN obtained an outstanding accuracy of over 90% for test input data throughout the model training phase.

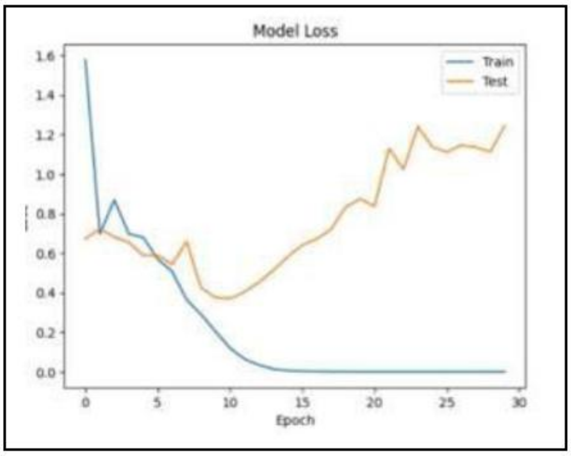

Figure 6: Accuracy of LSTM model

V. CONCLUSION

In Sri Lanka, very limited research has been conducted on the apparel manufacturing industry. 'Sew Smart' is a web-based solution that utilizes machine learning, image processing, and video processing to automate manual processes inside the apparel industry including detecting and analyzing data on garment errors, sewing machine proficiency, incorrect steps, and hand movements during sewing, and incorrect body postures of the training sewing operators. Automating those manual processes within training centers through 'Sew Smart' can significantly enhance accuracy and efficiency in the apparel industry's training procedures, consequently driving up success rates in production and yielding increased revenue streams.

Since this implemented application is related to the training process inside the garment industry, in the future, we have planned to expand the solution to the production sector of the apparel industry with a mobile platform.

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