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ML-Based Approach for Enhancing Sewing Operator Training in the Apparel Industry Using Hand Movement Recognition

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***Abstract* - In the apparel industry, the training of sewing operators plays a pivotal role in ensuring the production of top-quality garments. This research presents a novel approach to improve training methods through the implementation of a real-time hand movement recognition system. This system is designed to identify omissions and incorrect hand actions, providing immediate alerts based on Garment Standard Data (GSD) for prompt corrective actions. Leveraging advanced computer vision techniques and a graph neural network (GNN), the framework achieves an impressive 85.7% accuracy in monitoring and analyzing sewing operators' hand movements. By comparing detected movements with predefined standards, the system identifies deviations and offers instant feedback to operators. Experimental results underscore the system's effectiveness in pinpointing incorrect steps and hand movements, highlighting the potential of GNNs to elevate training in the apparel industry. The developed system significantly enhances sewing operator efficiency and productivity, ultimately leading to the production of higher-quality garments.**

Keywords: Sewing operator training, Hand movement recognition, Apparel industry, Computer vision, Graph neural network (GNN), Garment standard data (GSD).

I. INTRODUCTION

A pillar of the global economy, the apparel industry comprises of various sub-sectors and strongly influences social culture. Central to its success is the delivery of high-quality clothing to strict standards. However, existing manual training methods in the apparel sector hamper productivity, quality, and customer satisfaction by efficiently identifying and correcting sewing operator errors and hand movements. For more details, see [1],[2]. This research attempts to solve this dilemma by developing a real-time hand motion detection system tailored for MAS Linea Aqua, which aims to detect and correct mistakes and hand movements during the sewing process. Using computer vision and machine learning techniques, the system meticulously monitors and checks sewing operators' hand movements and ensures strict adherence to garment standard data. This research seeks to address gaps in the current training paradigm by increasing operator proficiency, increasing productivity, and establishing specific quality standards through immediate feedback and guidance.

Essential to this research is the use of a graph neural network (GNN) model to detect wrong hand movements and issue real-time alerts. For more details, see [3]. This approach departs from traditional RGB color-based methodologies and demonstrates a commitment to using advanced techniques for complex data analysis. It is important to note that previous attempts with an RCNN model yielded only 18% accuracy, primarily due to the model's inability to correctly identify fabric colors and stitch panel colors of sewing operators. In contrast, GNNs are known for their ability to reveal complex relational data, making them invaluable in deciphering the complex interdependencies inherent in a sewing operator's hand movements. The GNN model excels at recognizing only the skeletal structure of the human form. By adopting this modern methodology, one can not only increase the accuracy of the analysis but also gain a comprehensive understanding of the subtle relationships between the various elements, thereby significantly improving the quality and accuracy of the insights.

Through GNNs, capture the complex relationships of hand movements, facilitating the detection of deviations from standard garment sewing procedures and enabling quick correction of operator actions. By combining video processing techniques with GNN models, our research attempts to improve the accuracy and efficiency of imprecise hand movement detection in post-training sessions. Video data was acquired with a dedicated camera setup, and keyframes were extracted to focus on the sewing task, which involved sequentially lifting and placing garments with both hands. This approach improves the ability to detect deviations from

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standard procedures and errors in hand movements, making a significant contribution to refining sewing operator training.

The implementation of our system has the potential to significantly impact the industry. For instance, prior to the introduction of our system, MAS Linea Aqua relied on manual training methods, necessitating a 14-day training period with the assistance of job instructors. However, our system's ability to autonomously identify incorrect hand movements without the need for a job instructor is a game-changer. According to the feedback from the training center at MAS Linea Aqua, our system can reduce the time required for training, leading to a substantial reduction in training costs. Moreover, the system is projected to enhance production rates by approximately 12%, as it minimizes errors and ensures that sewing operators strictly adhere to industry standards. In the long term, this innovation also holds the potential to reduce the need for job trainer recruitment, further contributing to cost savings and operational efficiency.

II. LITERATURE SURVEY

In a study conducted by A.A. Yadav, Y. B. Kadam, S. D. Agashe, and M. S. Sutaone [4], the authors proposed the utilization of image-processing models to identify inaccuracies in hand movements performed by seamstresses. These models involved capturing photographs and converting them into frames, allowing for a more detailed analysis of the operators' motions. However, it is important to note that the authors acknowledged certain limitations of these models, particularly in their capacity to consistently capture the subtleties inherent in the stitching process. Their findings, as detailed in [4], highlighted the challenge of accurately detecting specific movements during sewing. To address these limitations, this study introduces an innovative approach that employs videos to identify imprecise hand movements in trainee sewing operators. This alternative methodology offers several distinct advantages when compared to the previous image-processing models. Videos provide a more comprehensive and dynamic representation of the entire sewing process, enabling a more in-depth analysis of operator movements. Moreover, video processing models possess the capability to assess the entirety of video footage, allowing for a holistic evaluation of sewing techniques and facilitating the provision of real-time feedback to operators.

Central to this research is the adoption of video processing models meticulously tailored for the analysis of video data. These models are designed to detect and track the intricate movements of sewing operators' hands, subsequently comparing them to a comprehensive database of known movements and sewing patterns. In the event of any deviations from the expected movements, the model triggers immediate real-time warnings, which are displayed to the operator. This approach holds significant potential in enhancing the training outcomes for sewing operators, as it furnishes them with valuable feedback pertaining to their stitching techniques, as well as their speed. Trainees can leverage this feedback to pinpoint areas for improvement and expedite their skill refinement process.

In the realm of hand gesture recognition, prior works, as cited in [5] and [6], have explored a system employing the Viola-Jones method, specifically tailored for applications centered around human-computer interaction. One common strategy in hand gesture recognition involves feature extraction from recognized objects, such as the hand, utilizing these features as inputs for a classifier. As elucidated in earlier references [5] and [6], Hu employed the Support Vector Machine (SVM) classifier to categorize instances of the hand, relying on invariant instance feature vectors. These Hu-invariant features were meticulously designed to capture crucial aspects of hand movement. Alternatively, deep learning techniques, notably Convolutional Neural Networks (CNNs), have emerged as a powerful means to autonomously learn features from input data. This approach has proven highly effective in various computer vision applications, including hand gesture recognition. The methodology discussed in the referenced studies demonstrates notable accuracy and suitability for human-computer interaction applications. However, it's important to note that this approach relies on hand-crafted features and the use of an SVM classifier, which may entail higher computational costs and potentially limits scalability when compared to deep learning techniques.

To address these limitations, researchers have ventured into exploring and testing a method focused on real-time detection of grasp gestures, leveraging the capabilities of the Microsoft Kinect device. Capitalizing on the Kinect's capability to precisely measure hand movements and detect hand-cup interactions, they devised an approach that exhibits proficiency in identifying grasp gestures. In this endeavor, depth data and the binary image of the hand, provided by the Kinect, were employed to train a Support Vector Machine (SVM) classifier, thereby further enhancing the accuracy of gesture detection. However, despite these advancements, the method is not without its challenges. One prominent obstacle lies in the accurate detection of non-grasp gestures, encompassing a broader spectrum of shapes and movements compared to grasp gestures. This diversity in variability can potentially lead to less accurate results, thereby influencing the overall effectiveness of the approach.

A study by R. Shrivastava [7] introduces an automatic recognition system based on Hidden Markov Models (HMMs)

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for identifying isolated gestures. The focus lies in distinguishing individual gestures through the temporal patterns captured by HMMs. While this method proves effective in recognizing discrete gestures, its scope might not extend to the intricacies of more complex activities. In comparison, the undertaken research delves into the nuanced dynamics of stitching processes and intricate movements, with the goal of encompassing a wider array of intricacies.

Another study by M. A. Khodher and A.-M. S. Rahma [8] presents a novel application of Hu moments, aiming to evaluate the degree of resemblance between two images. This innovative approach utilizes Hu moments as a comparative metric to assess the similarity between the image pairs.

Jingzhong Wang and Xiaoqing Xu present an advanced gesture recognition system[9]. It begins by capturing the hand-type region in an image using techniques like YUV color segmentation and image differencing. The images are then processed through contour detection and feature extraction using Local Binary Pattern (LBP) transformation and Principal Component Analysis (PCA). To classify the gestures, a Support Vector Machine (SVM) is employed as the machine learning algorithm. The experimental results with 630 gesture images show a significant improvement in recognition accuracy and speed, reaching an impressive recognition rate of 94.22%.

Another paper focuses on the challenge of maintaining a sterile surgical environment while effectively visualizing 3D medical images during operations. For more details, see [10] To address this issue, the authors propose an enhanced real-time gesture recognition system using deep convolutional neural networks and a Microsoft Kinect device. They developed a new dataset featuring 25 distinct hand gestures for deep learning, selecting the nine most accurate gestures for a touchless visualization system. The system, based on the AlexNet architecture, achieves an impressive recognition accuracy of around 96.5%, a significant improvement over previous methods. The paper also demonstrates the practical use of this technology for real-time touchless visualization of hepatic anatomical models during surgery, with the potential to improve patient outcomes by enhancing 3D image visualization in surgical procedures.

A study by Mygel Andrei and M. Martija[11], tackles the complex task of recognizing gestures underwater, facing issues like reduced visibility and challenging lighting conditions. They utilize the CADDY dataset to make significant contributions to the field: employing both traditional computer vision and machine learning techniques for underwater gesture recognition, as well as deep learning through a convolutional neural network (CNN) to improve accuracy. Their analysis includes a thorough investigation of which gestures are more challenging to identify using confusion matrices, and they compare the performance of these methods, with the CNN achieving an impressive accuracy rate of up to 97.06%. This work is among the earliest endeavors to apply computer vision and machine learning to underwater gesture recognition with the CADDY dataset, serving as a foundational benchmark for future research in this domain.

Video processing offers significant advantages over traditional image processing approaches when it comes to capturing and analyzing dynamic movements. By working with video data, researchers can obtain a more comprehensive understanding of the temporal dynamics and nuances of hand movements. Video data provides a continuous stream of frames, allowing for a detailed analysis of the progression and fluidity of gestures. This richer information enables a more precise assessment and evaluation of hand movements, ultimately leading to more accurate feedback and better training outcomes.

III. COMPARATIVE ANALYSIS

The system for detecting ambiguous hand movements of trainee sewing operators through video processing offers several notable advantages when compared to existing methods. In contrast to the approach in [4], which relied on image-processing models, using videos in the proposed system allows for a more comprehensive and detailed view of the operator's movements. Videos capture the temporal dynamics and nuances of hand movements, ensuring a more precise analysis of sewing processes and the detection of specific movements that might be missed by static image frames. The primary objective of the system is to aid trainee sewing operators in improving their skills through real-time alerts and immediate feedback. This feature sets it apart from methods such as the Viola-Jones method and Kinect-based approaches described in references [5] and [6]. While these methods are accurate, they may not provide real-time feedback, which is crucial for operators to promptly recognize and rectify their ambiguous hand movements. Efficiency in time analysis and reduced time complexity is another advantage offered by the system. Unlike some existing methods that can be computationally intensive, the system employs video processing models specifically designed for real-time analysis. This efficiency is particularly valuable in industrial settings, where quick feedback can enhance productivity and operator training. The proposed system offers a holistic view of the entire sewing process, distinguishing it from existing methods that may struggle with non-grasp gestures or capturing complex sequences. In contrast to these methods, the proposed system, based on video processing, provides a comprehensive

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perspective, allowing for a more accurate understanding of temporal dynamics and nuanced hand movements. This comprehensive view is crucial for improving operator skills. The adaptability and comprehensive understanding of hand movement recognition techniques are showcased by the proposed system. Reference [8] introduces Hu moments as a metric for image resemblance but mainly focuses on traditional gesture recognition. The proposed system, however, demonstrates the adaptability of these techniques beyond traditional gesture recognition. It offers a more versatile approach for capturing dynamic hand movements in the sewing process, resulting in a comprehensive understanding and better training outcomes.

IV. RELATED WORK

A) Machine Learning Approaches

Various machine learning algorithms have demonstrated their effectiveness in video classification applications. Support Vector Machine (SVM) has been widely employed as a common choice in many video classification studies. Additionally, convolutional neural networks (CNNs) have also been utilized, often involving the breakdown of videos into individual image frames for analysis. SVM has traditionally been applied to a wide range of video features or descriptors, making it a prevalent method in the field of video classification.

B) Deep Learning Approaches

GNNs are a type of neural network that can operate on graph-structured data, such as social networks and molecular structures. GNNs are designed to capture and model relationships between elements in a graph, enabling them to learn complex patterns and dependencies in data. By leveraging information from neighboring nodes in the graph, GNNs can effectively analyze and make predictions on sequential or spatial data.

C) GNN for Hand Movement Detection

Central to this study is the utilization of Graph Neural Network (GNN) models to effectively tackle the challenge of identifying erroneous hand movements in sewing operations.

The primary goal is to develop an automated system that can analyze video data and provide real-time warnings to sewing operators when their hand movements deviate from the standard or correct actions. The research follows a comprehensive approach involving several key steps. Firstly, a graph representation is constructed, where video frames or temporal segments are treated as nodes, and the edges capture temporal dependencies. The video data is then preprocessed, ensuring consistency and enhancing data quality through techniques like resizing, frame extraction, and normalization. The core of the research lies in designing and implementing a GNN model, which operates on the constructed graph, extracting meaningful representations and capturing patterns and relationships within the video data. The model is trained using optimization algorithms, minimizing a defined loss function, and updating parameters based on predicted and ground truth labels. Once trained, the GNN model is deployed for continuously processing the data and tracking the hand movements of sewing operators. By comparing observed movements with expected or standard actions defined in the dataset, the model can detect any deviations or incorrect actions and trigger warnings to the operator. The performance of the GNN model is evaluated using various metrics, assessing its accuracy, precision, recall, and F1 score. The objective is to contribute to the advancement of an automated system capable of refining the training process, boosting productivity, and ensuring top-notch garment production. This is achieved by adeptly identifying and offering feedback on erroneous hand movements during sewing operations.

The video processing method, coupled with GNN technologies, offers a promising approach to enhance training accuracy, consistency and productivity in the apparel sector. By harnessing the power of GNNs, which excel at capturing temporal dynamics and complex relationships in data, the system can accurately detect both correct and incorrect hand movements. GNN models are particularly well suited for this task due to the ability to analyze sequential data and capture dependencies and patterns in a graph structure.

The approach involves the collection of video footage of sewing operators performing various sewing operations, with a particular focus on tasks such as placing garment pieces on the sewing table. This video dataset serves as the training dataset for the system, providing a broad set of examples for analysis. Advanced computer vision techniques are applied to the collected videos to accurately capture hand movements. Advanced algorithms facilitate the identification and tracking of regions within video frames corresponding to the hands of sewing operators. This ensures precise analysis of hand movements during sewing operations.

The extracted hand movements are represented as a graph structure, where nodes represent specific hand positions or gestures, and edges capture the temporal dependencies between these movements. The graph structure serves as input for the Graph Neural Network (GNN) model. GNN uses its innate ability to capture temporal dynamics in the graph and analyze complex relationships, allowing accurate detection of correct and incorrect hand movements.

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The GNN video processing model offers a notable advantage in handling diverse video lengths and intricate action sequences. By capturing temporal relationships between frames, it efficiently analyzes and classifies extended or complex actions. Demonstrating promising outcomes in various video tasks, including action recognition and event understanding, the GNN model's utilization of spatial and temporal data ensures robust video processing. This versatility finds applications in domains like surveillance, sports analysis, and human-computer interaction.

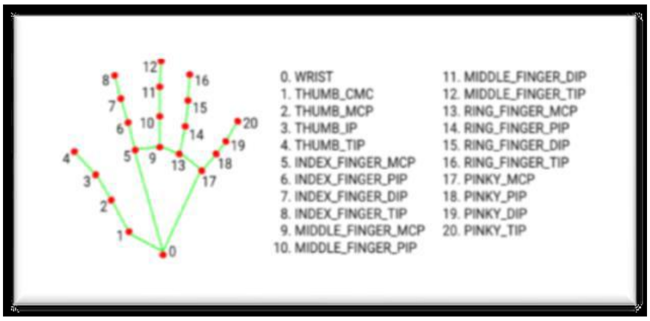

Figure 1: Landmarks for real-time hand gesture recognition
Source: researchgate.net

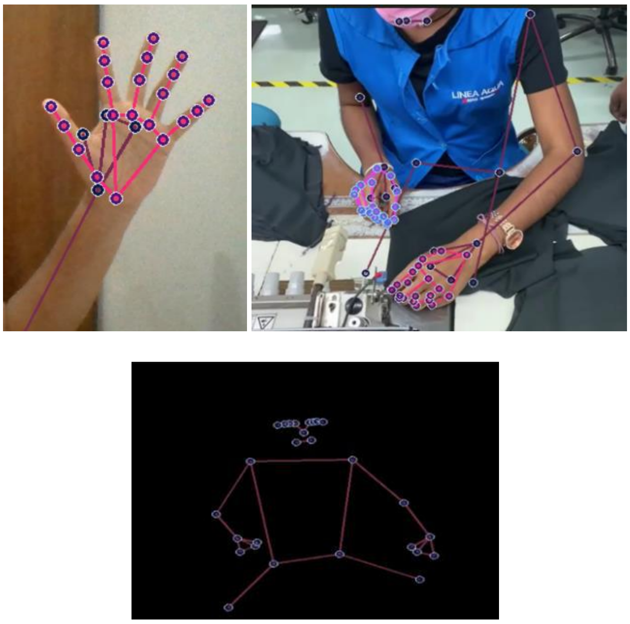

Figure 2: Acquired landmarks for real-time hand gesture

V. THE PROPOSED SYSTEM

Through the integration of computer vision techniques and the GNN model, the approach detects and categorizes inaccurate hand movements within the sewing operations of MAS Linea Aqua. The immediate feedback it offers, along with its alignment with Garment Standard Data, holds the capacity to notably enhance training results and elevate the efficiency of sewing operations within the garment industry.

- Hand Movements Detection: Video footage of sewing operators engaging in particular tasks, like positioning garment pieces on the sewing table, is captured. Subsequently, computer vision algorithms are employed to analyze video frames, identifying and categorizing hand movements.
- Graph Neural Network (GNN) Model: Leveraging a GNN model, the methodology represents video frames in the form of a graph structure. The GNN effectively considers temporal dependencies among frames, adeptly capturing intricate relationships to precisely recognize flawed hand movements.
- Garment Standard Data Compliance: Detected hand movements are juxtaposed against the predefined Garment Standard Data to verify operators' adherence to established guidelines. Any inconsistencies or erroneous motions are promptly identified, leading to corresponding feedback provided to the operators.
- Automation and Efficiency: Through the automation of incorrect hand movement detection, the approach diminishes the necessity for manual training interventions, thereby enhancing the overall efficiency of the training procedure. Operators are furnished with feedback that aids in rectifying errors, consequently expediting skill refinement.

VI. METHODOLOGY

The system's methodology is primarily focused on the detection of incorrect hand movements during sewing, with a pivotal role played by the innovative Graph Neural Network (GNN) model. The approach involves comprehensive data collection, preprocessing, computer vision techniques, and real-time monitoring, all geared toward ensuring precise analysis of trainees' hand movements and adherence to garment standard data. Data collection involved acquiring correct hand movement data and two types of incorrect hand movements, maintaining equal data proportions for each class, all stored in MP4 format. Subsequent preprocessing steps included frame extraction and resizing to prepare the video data for analysis. The heart of the system lies in the application of computer vision techniques for real-time monitoring and precise tracking of trainees' hand movements, ensuring that they align with established industry standards. The system compares detected hand movements to a reference model, providing immediate feedback to trainees when discrepancies are identified.

The choice of the GNN model is a key highlight of this methodology, as it represents sewing operators as nodes and their connections as edges in a graph structure. This approach minimizes reliance on RGB color information and is particularly effective in analyzing sequential hand movements.

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A carefully curated dataset of 300 videos was used, split into training and test sets to train and evaluate the GNN model. The GNN's ability for sequential hand movement analysis enables the detection of subtle changes in hand positioning and gestures, contributing to the improvement of sewing operator skills. In essence, this holistic methodology combines data collection, preprocessing, computer vision techniques, and the power of the GNN model to enhance monitoring and compliance with industry standards, ultimately fostering the growth and development of sewing operators within the garment industry.

VII. RESULTS AND DISCUSSIONS

Developed a machine learning model using the Graph Convolutional Network (GCN) architecture. The input data has a size of [93, 3, 10], where 93 represents the number of samples, 3 is the number of input features, and 10 is the length of each feature. The model consists of three GCN layers: conv1, conv2, and conv3. The conv1 layer takes an input of size 30 and produces an output of size 64. Similarly, conv2 and conv3 take an input of size 64 and produce an output of size 64 as well. These convolutional layers are responsible for capturing and extracting relevant features from the input data. The model also includes a linear layer (lin) that takes the output from the final GCN layer and maps it to a 2-dimensional output, using a linear transformation.

During the training process, the model is trained for 100 epochs, and the training accuracy achieved is 0.8529, indicating the model's ability to predict the correct labels for the training data. The test accuracy achieved is 0.8571, which represents the model's performance on unseen data. The model's training loss at this epoch is 0.3644 indicating the average discrepancy between the predicted labels and the ground truth labels during training. Overall, this GCN-based model demonstrates promising capabilities for analyzing graph-structured data and making predictions based on the extracted features. Further optimization and fine-tuning may be required to improve its generalization performance on unseen data.

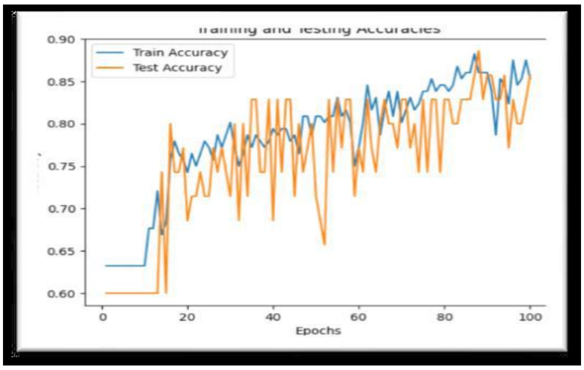

Figure 3: Training and Testing Accuracies

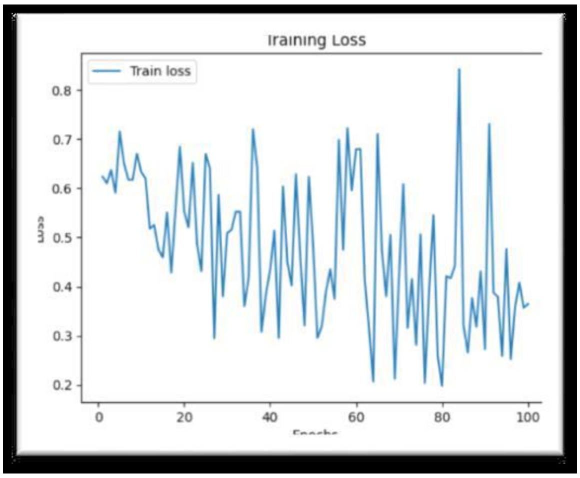

Figure 4: Training Loss

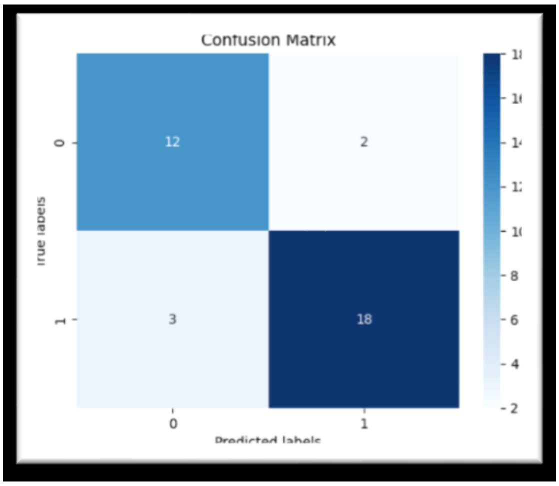

Figure 5: Confusion Matrix

VIII. CONCLUSION

This study presents an inventive method to improve sewing operator training and performance in the garment industry. Using an automated hand movement detection system based on computer vision and the Graph Neural Network (GNN) model, it accurately identifies incorrect hand movements as per Garment Standard Data. The system's benefits encompass feedback provision for error correction, efficiency enhancement, reduced training time, and increased productivity. Integration of the GNN model enables capturing temporal dependencies and analyzing complex relationships, ensuring accurate detection.

IX. QUANTIFY INDUSTRY IMPACT

The system can lead to significant industry impacts, including cost savings, error reduction, and production rate increases. It has the potential to reduce training costs and lower the need for rework, resulting in cost savings. Error rates during the sewing process can be decreased, and the system's efficiency improvements can contribute to higher

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production rates. To provide specific quantitative values for these impacts, further analysis, and data collection during system implementation in a real-world sewing environment would be necessary to measure the system's industry impact accurately.

X. FUTURE SCOPE

In the context of GNN models, there is still room for exploration and innovation. Future research can focus on developing hybrid techniques that combine CNN and GNN architectures, leveraging the strengths of both approaches. This hybridization can potentially enhance the accuracy and robustness of action classification in videos. Additionally, research efforts can be directed towards optimizing GNN models specifically for the analysis of hand movements in sewing operations, aiming to achieve even higher accuracy and real-time performance. By harnessing the power of GNNs, significant advancements can be made in detecting incorrect hand movements and providing real-time warnings, ultimately improving the skills and efficiency of sewing operators in the garment industry.

Highlight the potential for scaling up the developed system to include all the different parts of the garment manufacturing process, providing comprehensive real-time analysis and feedback to sewing operators. The system can be further enhanced by integrating additional features, such as posture detection and speed analysis, to provide a comprehensive assessment of the sewing operators' performance. Additionally, the system can be extended to monitor sewing machine activities and enhance overall process monitoring in garment factories.

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