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A Secure Framework for Analyzing Customer Behavior Using Quaternion Graph Attention Network

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Abstract. *The complicated interconnections of spatial-temporal data safety of many of smart retail environments which that build on video test to recognize customer behavior signify a primary challenge. The enormous amounts of visual data from surveillance cameras are not used effectively. The objective of the study is employing sophisticated computer vision methods using quaternion transform DQFT and Graph Attention Networks GATs, to create secure intelligent model for analyzing customers' behavior using video data in smart shops. The proposed work creates videos of person captured inside the store. Then, customers are detected and tracked over time to extract moving paths. To improve recognition of motion, customers moving around the store are recorded and transformed into a four-dimensional exhaustive DQFT. Next, diagram illustrates customer's motions inside the store is constructed, where nodes represent places and edges to transfer between nodes. GAT model is tested to examine the graph; also it classifies the behavior of customer into undecided, direct, and snooping. Security layer is utilized for ensuring the privacy through face blurring and characteristic encryption. The outcomes of the model are more accurate than conventional when applied to forecasting behavior in_ store, achieving over 99.1% accuracy in classifying customer behavior compared with CNN and GCN. The suggested framework reaches (recall = 98.2 and FPR = 0.01) in purchasing predicting. The integration of suggested model with security will promote the potential of retail systems employing artificial intelligence.*

Keywords: Behavior Analysis, Computer Vision, Customer Privacy Security, GAT, QT, Smart

1 Introduction

Background and Significance of the Study

With the start of smart retailers relying on technologies of artificial intelligence and computer vision to understand the behavior of customers and increase their inventory knowledge, the shopping situation has rapidly altered toward digital transformation. Beyond just showcasing products, these businesses track customers' actual relations with objects and their journeys, enabling them to make data-driven marketing [1]. A customer's behavior in a store has a significant influence on how well its design and product location efforts work. The tactics of marketing can develop, contribute to better internal design, and

enhance sales through tracking the movements of customers, empathizing with their regions of interest, and analyzing the relationship with goods. Additionally, behavior analysis improves the stock's human resource allocation in terms of time and tasks while also providing personalized recommendations [2-3]. The fast expansion of computer vision and artificial intelligence techniques has made it possible to observe how people behave inside intelligent sites like marketing establishments. The investigation of this behavior will assist in improving strategies of marketing, distribution of production, and the shopping experience [4].

Problem Framework

Many prior studies commonly utilized conventional neural networks (CNNs), which suffer from limited ability to designate interactions between temporal and spatial. GCN algorithms deteriorate from computational slowness with big data and lacks weights allocation to the most important behaviors. Recurrent networks (RNNs) and convolutional neural networks (CNNs) are the basis of the common conventional models in behavior analysis [5-6]. Although, these techniques find out photos and videos, they suffer in representing the dynamics interchanges between successive motions within a stock. Consequently the accuracy is minimized because these approaches fail to determine behavior as spatiotemporal structure [7].

Originality of the work

The present work utilizes Graph Attention Networks (GATs) and quaternion transformations (QT) to improve performance of the model. The study offers a different and inspired model to analyze client behavior by joining two methods: Graph Attention Networks (GAT) to investigate the relationships among customer movements within a store via a graph, and the Discrete Quaternion Fourier Transform (DQFT) to extract movement features from video. The attention method permits a universal description of customer motion by focusing on the most salient aspects of behavior [8-9]. This study aims to form an intelligent model to analyze video using the Quaternion transform, building a graph that displays the movement of customers, discovering behavioral patterns, classifying them by GAT, and helping managers in constructing choices inside smart shops to present the analysis's outcomes in an interactive and visible design [10].

Cybersecurity has become a vital component in the configuration of smart

systems attributed to the increasing reliance on AI smart systems in retail environments. Processing video data requires data security, which guarantees privacy and safety. Thus, integrating reliability and security mechanisms increases the applicability of smart systems and user trust in the real world [11-12].

GAT (graph attention network) is a category of neural networks that is designed to process data represented as charts. After finishing jobs like classification of nodes or calculation of links, GATs use the idea of attention mechanisms for understanding the importance of unlike nodes in a graph [13]. GATs can emphasize the importance and influence of components across graphs by assigning weights to adjacent nodes. GAT is an improved variant of GNNs that assesses each neighbor's significance by updating procedure using a technique identified as attention [14-15]. GAT is one of the deep learning mechanisms that depends on GNN and utilizes an attention method to determine how much importance weight to assign to each edge during updates to the node. The steps of GAT are summarized as follows: first, represent the graph by nodes and edges. Secondly, compute attention coefficients for each neighbor using the ReLU function. After that, gather neighbors' representations of nodes based on their importance weights [16-17].

The quaternion transform utilizes quaternions more than real or complex numbers; QT is a mathematical extension of the classic Fourier transform that provides a structure for describing multidimensional data (including color, motion, and rotation). Each color or dimension of motion is represented as an element of a quaternion in the Fourier transform, which is proposed for signals or images with multiple channels, such as RGB [18-19]. It permits the signal to be transformed and analyzed while preserving the relationships between the channels. Regarding its important applications, well-known ones include: analysis of RGB images, illustration of object motion, examination of multichannel video, and robotics and navigation systems [20].

Paper Organization

This framework is broke up to five essential parts. Section 2 presents earlier studies of behavior analysis in artificial intelligence, while Section 3 shows the proposed model and its practical phases in detail. Section 4 displays tests of experiments and performance valuation,

where Section 5 proposes conclusions and recommendations for the future.

2 Related Work

Various studies have examined the behavior of customers using conventional approaches such as convolutional neural networks (CNN) and camera-based body tracking. The former studies presented GAT to analyze marketing or social graphs, whereas QFT is used to process images and videos. However, the dynamics of customer motion within a store are not given attention in these methods. The Graph Attention Methodology (GAT), which provides this study with a novel approach, has not been utilized in any of the limited research that has employed graphs as an implementation to model customer's movement. In this study, graph attention networks (GAT) and (QFT) are utilized to analyze customer behavior in smart shops.

Rubing *et al.* [21] proposed a novel framework to forecast decisions of customer buying using video data. They proposed four main challenges in the traditional method of purchase for customer estimation: taking customer behavior in actual time, applying automation and scalability, combining of multidimensional data, and preserving the natural customer without affecting the shopping. Hu *et al.* [22] presented an interactive method to gather customer comments and opinions . They collected and estimated the expressions of faces using an enhanced deep neural network DNN. The suggested model IDNN-CBA is trained and achieves 96.55% accuracy on the KAGGLE dataset. Zhu *et al.* [23] proposed GAT with context-aware heterogeneity for forecasting of user behavior on a service platform for local customers. CHGAT is proposed to assess the probability of future behavior and to generate a dynamic representation of the user. They construct networks of heterogeneity using meta-paths with former behaviors. Then, they presented an attention-based multi-level approach for context-aware combination with the graph vertices, comprising attention from the path-level network and the vertex-level network.

Xu and Qu [24] presented self-GAT, which utilizes data mining of student behavior to extract trends from data on buying and teaching. In the beginning, they built a graph with a topological structure from the data they were consuming. Then, they suggested an improved model of the GAT mechanism. After that, they determined the taxonomy tasks of academic performance and identified learning patterns consecutively

and behavior of life. Building on the outcomes, the accuracy of the two-type taxonomy was 84.86%, whereas the three-type taxonomy reached 79.43%. Venegas *et al.* [25] presented techniques for quaternion_ based processing of color-synthesized thermography using NDT. They suggested a novel method for analyzing thermal data to extract a large amount of information from recorded series. To raise the discovery level and simplify error classification, the extracted data is combined into three frequencies, which can be clarified by images of physical color and processed using techniques of quaternion algebra. Table 1 illustrates a list of related studies.

Table 1 Analysis of related works and suggested work

Study	**Technique**	**Studying Focus**	**Limitation**
[21]	Techniques of transformation	Investigating customer activities using video data	Limited data and high computing ability
[22]	Deep Neural Network with visual techniques	Investigating customer performance using an enhanced DNN	Limited data and environment
[23]	Heterogeneous Graph	Analyzing users' interactions and selecting more relations of context	Limited environment and high computing ability
[24]	GNN	Building a performance network for examining students' consumption inside the university.	Limited data, overfitting, and generalization.
[25]	Quaternion transforms for enhancing thermal images.	Enhancing optical quality for thermal output of color images	This study utilizes a limited number of images and does not merge with machine learning.

Research Gab

According to a researcher's previous study, most studies have focused on employing GCNs, GATs, or CNNs to study customer behavior. The analysis of customer behavior has not been directly promoted by the combination of QT with GAT, despite a few efforts to employ quaternion representations in different areas.

Thus, the significance of this work rests on addressing a knowledge gap through the construction of novel schema that leverages the strengths of GATs to highlight the adaptive weights of customer-product relations and the skill of

QT to numerically embody composite, multidimensional associations. Consequently, it is expected that the paper will enhance the accuracy of forecasting patterns of purchasing behavior and will offer a contemporary qualitative influence on academic work in the fields of customer behavior investigation and artificial intelligence.

3 Methodology

3.1 Study Design

This paper develops a hybrid model that enhances the accuracy of customer behavior prediction in smart stores by combining QTF, which extracts a representation of spectral motion, and GAT, which detects behavioral patterns via attention-based analysis. In this work, GAT is proposed to examine the behavior of customers in a store, where each node represents a product or site, and each edge denotes a customer's movement between two spots. Some of the important motions, such as standing in front of a product for period, are more important than others, which helps to select the GAT network in this paper.

Table 2 Customer Behavior Analysis Data and Stay Period

Customer ID	**Video ID**	**Enter time**	**Exit time**	**Stay duration (m)**	**Interact with the product**	**Purchase decision**	**Waiting time for payment**
Cus1	Vid1	1:10	2:35	85	Touch	yes	30
Cus2	Vid1	12:30	1:30	60	See only	No	0
Cus3	Vid2	9:05	10:15	70	Reading the label	Yes	25
Cus4	Vid2	11:05	12:45	100	Touch and reading the label	Yes	30
Cus5	Vid3	12:45	2:45	120	Touch and examine	No	0
Cus6	Vid3	2:15	3:10	55	Reading the label	Yes	15

Table 2 represents the essential components of small sample of customer behavior analysis spreadsheet template when analyzing a video. Customer ID (Cus) is a symbol denotes a serial number

for each individual in the video to identify them and track their movement. Time stamp represents the time at, which customer enters or exits. The interaction field denotes did the customer interact with the product, for instance, by touching it or reading information about it? The decision of purchase field denotes whether the behavior converted to an actual purchase or leaving without purchase.

The first stage of data gathering is data acquisition, which starts with capturing HD video by monitoring the camera in the store. Then, computer vision processing is utilized to separate background, detect customers by bounding box and put ID number for each customer. QT takes the 2D joint coordinates and projects them into 3D. The orientation vectors express hand gestures and body orientation of the customer toward the shelves. GAT emphasizes these important intentional motions and improves behavioral classification. This paper utilizes a QTF to extract speed and direction from videos recorded by a camera inside stores and to analyze them. Then, the trajectories are altered to a graph that represents points of movement and transition. Based on the attention given to each transition point, a GAT network is used to evaluate the graph and identify behavioral trends.

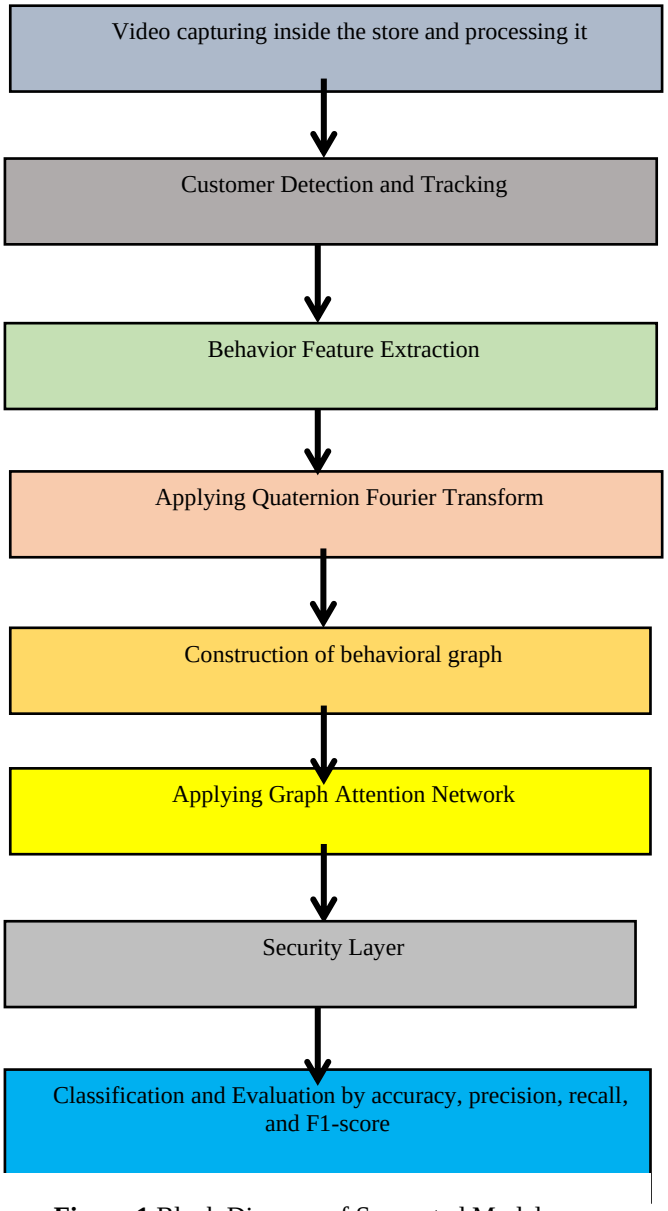

Figure 1 Block Diagram of Suggested Model

The Quaternion Transform (QFT) is utilized to find out movement gestures. Spatial tracking data are extracted from the video like position, direction, velocity, and time. These data are altered to quaternion frequency through QFT, which represent object motion in 3D space. The outcomes appear as spectral matrices that

precisely capture the nature of motion in both space and time. After that, the results are converted to a graph, which GAT analyzes. All nodes in the network indicate a certain motion of the customer, such as stopping or backing away. The relationships between movements are denoted by edges, for example, stopping after approaching a quick change, etc. GAT employed an attention approach to determine the vital actions in a chain of behavior, such as the uncertain, surveyor, and direct purchaser. Figure 1 explains the proposed method, which takes a video of customers in the store and converts its frames into images. Then, apply QFT to the images and extract spatial-temporal information. After that, represent each customer by a node, and the edges between nodes represent (behavior, location, and time). GAT analyzes the graph, and the customer is evaluated using metrics, with the results interpreted to inform decision-making using the attention mechanism.

3.2 Algorithm Design

Algorithm 1 outlines the key stages for a secure system for customer behavior prediction using the Quaternion Fourier Transform (QFT) and Graph Attention Networks (GAT).

Algorithm 1: Framework of behavior prediction

Input: Video Frames of Customers
Output: predicated customer behavior

1- Obtain a stream of video from the monitoring system.
2- For each frame:
-Preprocessing, such as normalizing, resizing, etc.
- Detect the customers, track them, assign unique IDs, and excerpt the key joints of the body or object.
3- Apply security measures that includes face blurring and ID anonymizing.
- Building vectors of features for each frame.
4 - Apply QFT to:
- Transform spatial features to the quaternion domain.
- Build a matrix of features using spatial–temporal coding.
5- Building a graph where:
- Nodes denote the main points of the body for each frame.
- Edges represent the relations between nodes.
- The weight of the edge signifies the motion of the customer.
6- Feeding the graph to GAT:
- Applying a self-attention mechanism to learn nodes.
- Gathering information using weights.
7- Applying Softmax to predict customer behavior
8- Evaluate the model using performance metrics

Figure 2 displays customer behavior prediction using Graph Attention Networks for video surveillance, which shows the movement of persons in a store. Then, customer movements are observed and converted into time points. GAT focuses on a person's attention, such as a customer stopping, looking at a certain shelf, or changing directions. GAT assigns points based on the significance of behavioral factors, in addition to that the consecutive sequence. The proposed work is developed by adding Cybersecurity and

trustworthiness of results. For ensuring the personal data protection of customer and avoiding the storage of video data, this work implemented anonymization and privacy-preserving techniques by encrypting recognizing information.

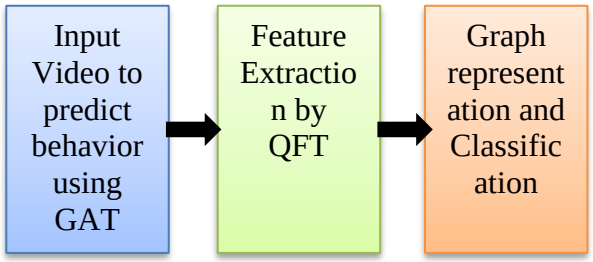

Figure 2 Stages of Behavior Analysis

Noise injection was applied to the behavioral personalities extracted during training to improve the model's robustness and its handling of imperfect data. This decreases the model's sensitivity to anomalies caused by tracking errors. Moreover, to improve the training stability and diminish overlearning, the dropout method was utilized. This is to improve the model's reliability in real environments.

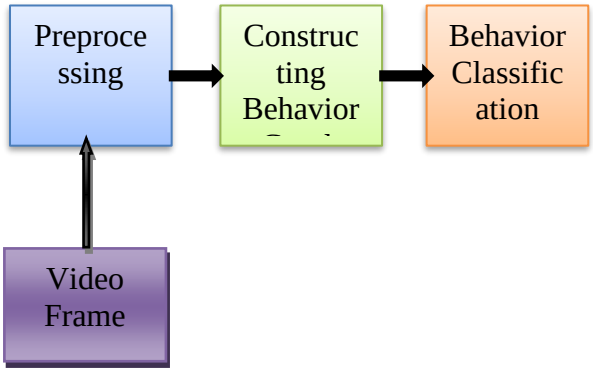

Figure 3 Proposed Method for

3.3 Data Preprocessing

In detail, there is a group of key phases in the recommended model, as clarified in Figure 3 and Figure 4:

1. Preprocessing stage

• Using a smart camera can capture video within the store and gather it.

• Extract frames from the video.

• Reduce noise and normalize.

• Identifying the directions of movement of the customers through a DQFT (Quaternion Transform) for each frame.

2. Detect customers and track trajectories.

3. Building the Graph Behavior stage

• Signifying the movement of customers inside a store as a graph:

• Nodes signify locations in the store.

• Edges represent the movement of customers between sites.

• Weight indicates interaction with a product.

4. Executing GAT (Graph Attention Network)

• Applying the algorithm to the graph

• Emphasis on the movements of customers and significant locations.

• Provide better weights for relations with stronger behavioral importance.

5. Security Layer

• Privacy maintenance, keeping personal data of customers and not storing data.

• Noise reduction decreases the responsiveness of the model to noise and errors in the training set.

• Dropout, enhancing stability of training, and decreasing overlearning.

6. Classification of Behavior

• Labeling customers into behavioral classes like

• Inquiring Customer

• Undecided Customer

• Influential Customer

• Producing an interactive description to help the administration in decision-making.

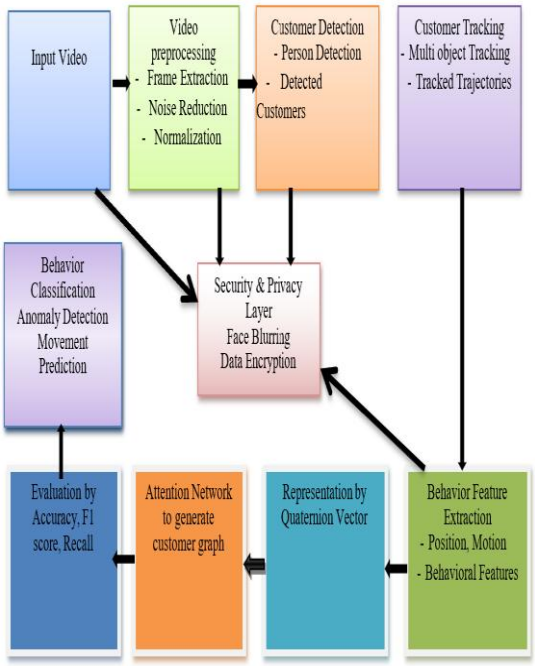

Figure 4 Architecture of Proposed Secure Intelligent Retail System of Customer Behavior

The components of hardware system are laptop Core i5 processor, 32 GB RAM, and RTX 3060. The software system constructs on Python 3.10, with Tensor Flow and Scikit-learn for tests of intelligent learning. The metrics were utilized for model performance, accuracy, precision, recall, F1-score, false positive rate. This work was estimated in a 48-hour to attain optimal outcomes.

4 The Results and Discussion

This part reviews the outcomes of the presented model (QFT + GAT) and it compares them with traditional methods such as GCN and CNN that perform for

classifying customer behavior in smart shops. To study the accuracy of classification for each behavioral class, a confusion matrix is also involved, as in Table 3

Table 3 Confusion Matrix of the Suggested Model

The model	Accuracy	Recall	F1-score	Precision	Processing time
CNN	80.1%	78.2%	79%	81%	110ms
GCN	83.2%	82.1%	83.1%	84.2%	60ms
GAT+QFT proposed	99.1%	98.2%	92.2%	99.1%	25ms

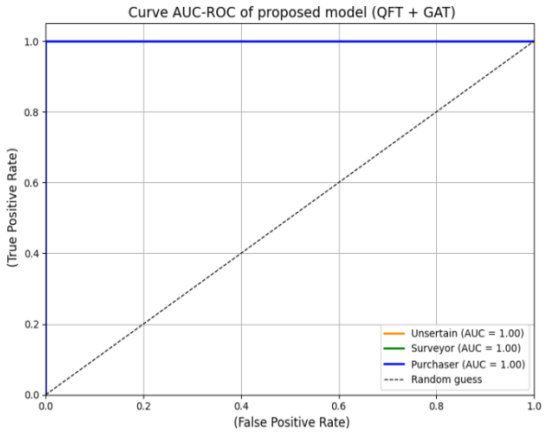

Figure 5 AUC of Categories of Customer

Figure 5 displays AUC-ROC curves for three customers' behavior categories: uncertain, surveyor, and purchaser. Each line represents the model's performance in differentiating between the objective fragment and the other parts. The model's accuracy increases as the curve approaches the upper-left corner. The graph displays that the area under the curve (AUC) of the model is high across the board, indicating excellent classification performance and high accuracy in predicting customer behavior.

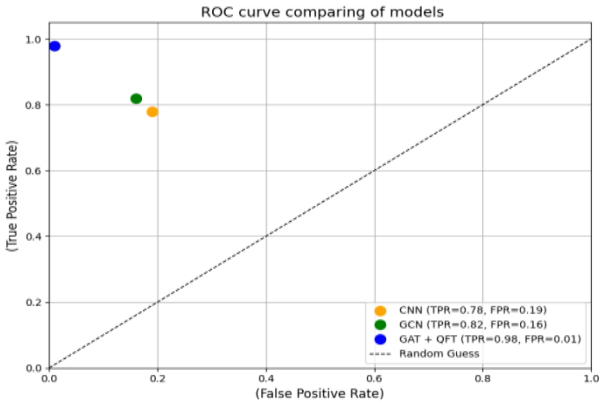

Figure 6 AUC-ROC Curves of Three Models

These outcomes indicate that the proposed model (QFT+GAT) is suitable for applications in video analytics or behavior observation in smart stores, as it can excellently distinguish between various patterns of customer behavior. Figure 6 displays a ROC curve comparing three models of classification (CNN, GCN, and the proposed GAT+QFT). The horizontal axis (FPR) represents the proportion of undesirable (negative) samples that were incorrectly categorized as positive. The vertical axis (TPR) illustrates how well the model detects positive samples (recall). The CNN model performs well, but it has a high prediction error.

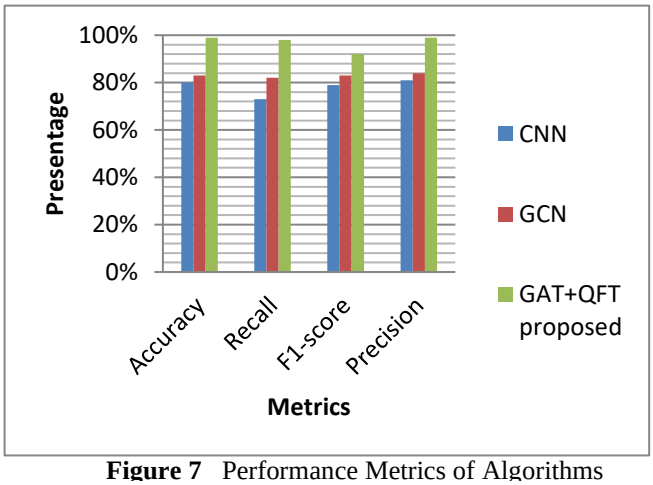

Figure 7 Performance Metrics of Algorithms

The evaluation process was tested with CNN, GCN, and (GAT& QFT) algorithms. It is obvious from Figure 7 that the accuracy of the suggested model was 99.1%, Ninety-eight point two percent of recall, 92.2% of precision, and 99.1% F1-score. The performance of the GCN model is better than the CNN, with higher recall and fewer false positives. The GAT+QFT model achieves a recall of 0.98 and a very low false positive rate (FPR = 0.01), which is considered an excellent classification result.

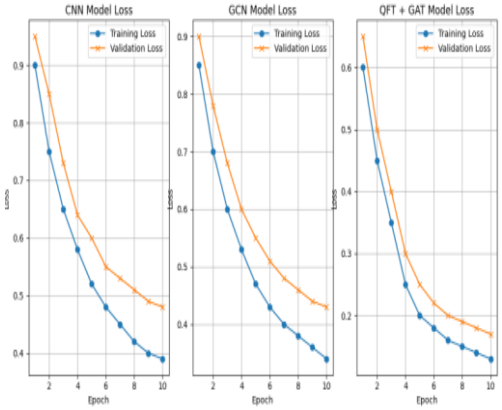

Figure 8 Comparative Analysis Graphs for Models

Figure 8 displays the training and validation loss for three models. In the CNN model, training loss starts at 0.9 and then gradually decreases to 0.39. Also, the validation loss decreases slowly from 0.95 to 0.48. GCN is better than CNN, training loss improves from 0.85 to 0.34, while validation loss minimizes from 0.9 to 0.43. The proposed model QFT + GAT greatly decreases from 0.6 to 0.13, while the validation loss minimizes from 0.65 to 0.17. From the results, the QFT+GAT moc er moc

Table 4 Comparing the Suggested Model and Traditional Methods

Actual/estimated classification	Uncertain	Surveyor	Purchaser
Uncertain	45	0	0
Surveyor	0	20	1
Purchaser	0	0	45

Table 4 shows that compared with conventional approaches, the suggested model outperformed them in terms of general accuracy and F1-score. The purchaser classification error ratio is lower, indicating the model is effective at detecting buying. This model correctly categorized 45 customers as uncertain. It misclassified 0 of them as surveyors and 0

as purchasers. Likewise, it accurately categorized 20 surveyors, but misclassified 0 and 1. Purchasers' accuracy was highest 45, with 0 and 0 incorrect cases. Figure 9 displays performance metrics of customer behavior.

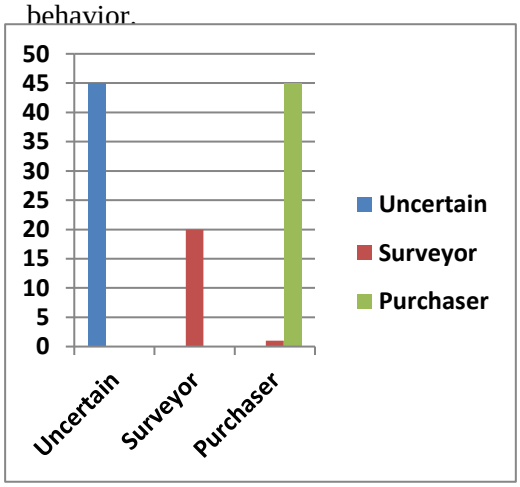

Figure 9 Performance Metrics of

The performance of work was assessed in an experimental stock situation and compared with that of CNNs. At almost 99.1%, the outcomes were presented excellently based on accuracy. Through the convention of the mechanism of attention involved with GAT, the model displayed the capacity to identify regions of interest within the shop, and patterns of interaction can be analyzed in more detail. A GAT network will be utilized to categorize behavior and assess the graph with an attention technique that highlights the most significant relationships.

5 Conclusion

In this study, a novel mechanism was presented by combining GAT with QFT to improve the description of the temporal and spatial environment of human movement within a smart retail. Graph Attention Networks (GAT) and Quaternion Transform (QFT) models are proposed to extract movement features from video by analyzing behavioral graphs. The model validated the effectiveness of the customer's investigative behavior in smart shops through development and non-traditional approaches. Based on performance metrics, the QFT+GAT suggested model executed better than the conventional CNN and GCN models, achieving 99.1% accuracy compared to 80.1% and 83.2%, respectively. QFT assists in representing complex movement and extracts fine details from movies and videos, thereby improving the quality of data for graphical investigation. GAT focuses on entities with flexible methods, such as customers or objects that have the greatest influence on entity behavior. Low values of loss denote that the model does not suffer from overfitting, demonstrating that it can be applied it in a real-world setting within smart workshops.

In the future, we suggest expanding the deployment of the GAT network and improving processing speed in realistic applications within the sites of large stores.

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