Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

HyViSE: (Hybrid ViT-SE) Approach for Crowd Anomaly Detection and Emotion-Behavior Classification

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ARTICLE INFO

Received: 17 Oct 2024

Revised: 10 Dec 2024

Accepted: 26 Dec 2024

ABSTRACT

The ability to gauge emotional states through motion data is a prominent research topic within affective computing as well as crowd behavior analysis. This paper describes a hybrid model named HyViSE: (Hybrid ViT-SE) that improves the feature extraction and attention mechanisms. This proposed model contains convolutional neural networks (CNNs) for local feature representation, Vision Transformers (ViTs) for capturing long-range dependencies, and SE blocks for adaptive recalibration of feature maps. This model proposes to combine convolutional neural networks (CNNs) for learning local feature representation with Vision Transformers (ViTs) for long-range dependencies and SE blocks for adaptive recalibration of feature maps. Thus, the fusion of CNNs and ViTs lets the proposed model gain from the benefits of both architectures which, in turn, makes the system a more powerful and generalized one. From local feature extraction, CNNs analyze fine details in the image with a relatively high degree of accuracy, while ViTs enable a broader understanding via the consideration of the holistic context from the entire image. The SE blocks dynamically recalibrate the importance of feature maps so that the most salient features are weighted over the others, which would further enhance the performance of the model. The proposed model applied on Motion Emotion Dataset (MED) and able to achieves an accuracy of 99.21% on the emotion dataset, which includes 7 different classes, and 97.08% on the behavior dataset, which has 6 different classes. The models are validated using a confusion matrix.

Keywords: CNN, ViT (Vision Transformer), Squeeze-and-Excitation (SE), Motion Emotion Dataset (MED)

INTRODUCTION

The crowd, meaning any aggregate of people stationed at a particular site, derives its characteristic from the context under consideration. For example, the composition of crowds in a temple will be present for a completely different reason than crowds in a shopping area. The term 'crowd' is contextually applied, taking into account parameters like number of people along with time spent, composition of people, cohesion, motivation, and the physical distance between individuals. These factors really need an understanding to gear up and prevent any possible critical situations from arising [1].

Current global overtly tilted possibility of overpopulation is inviting scenes of overcrowding in many cities and situations tend to arise during events such as parades, station entrance and exit, political demonstrations, and strikes that give rise to significant security-related concerns [2]. More and more cities across the globe are putting into practice their own surveillance systems with the aid of video-monitoring cameras [3]. In the beginning, human agents supervised these systems; however, this method was found to be less effective, more prone to errors, and increasingly overburdened over time [4]. Some more recent literature on aspects like mob lynching [5], protests regarding the CAA bill [6], revocation of Article 370 [7], violence in several universities in India [8-10], and a riot-like atmosphere created during the invasion of Delhi's Red Fort by farmers during a huge tractor parade [12] clearly exemplify why and how desperately automated crowd behavior analysis is needed. The very existence of crowd surveillance systems serves to detect abnormal occurrences within public places, a crucial asset to different stakeholders needed to counter the major security threats faced by society at large [11]. Video Anomaly Detection (VAD) plays a crucial role in intelligent surveillance systems, allowing for the identification of unusual events within video frames either temporally or spatially.

However, current methods for video anomaly detection encounter several significant challenges. The foremost issue is the limited emphasis on multiclass anomaly detection. Many models are designed primarily for binary classification tasks (normal vs. anomalous) and do not effectively differentiate between various types of anomalies [13]. This limited approach diminishes the effectiveness of such models in real-world scenarios, where it is essential to identify specific types of anomalies (e.g., theft, vandalism). The second challenge is obtaining high performance metrics for both multiclass and binary tasks [14]. Class imbalance is another big challenge, with anomalous events occurring far less than normal activities. This gives rise to imbalanced class distributions detrimental to model performance. In addition, scalability is a big concern considering that handling enormous amounts of video data calls for models that can process information in a swift manner without compromising on accuracy. Solving these challenges is vital, with the aim of creating anomaly detection systems that would work accurately and also cater to practical applications in the real world. In large-scale crowds, individuals can be categorized based on their emotional states, such as anger, happiness, excitement, sadness, and other emotional effects. These emotions significantly influence crowd behavior, leading to classifications like panic, fighting, congestion, and more. To address the multi class classification various approaches are applied on the datasets like UCF Crime, Motion Emotion Dataset (MED), UCSD Pedestrian Dataset, Avenue Dataset and significant efficiencies are achieved.

Pre-trained CNN models such as EfficientNetB7, DenseNet121, InceptionV3, MobileNetV2, and VGG19 are utilized for human activity recognition in surveillance systems, performing moderately well on multiclass datasets. These models demonstrate efficiency across key metrics, like training and validation accuracy, training and validation loss, when applied to a publicly available Human Activity Recognition dataset. Additionally, the study aims to investigate how factors like model complexity, training time, and computational efficiency influence the practical deployment of Video Anomaly Detection (VAD) systems in real-world scenarios. In this direction, this research will contribute to defining own CNN model for enhancing the effectiveness and efficiency of surveillance systems, and ensuring it operates optimally in diverse and dynamic environments. These models alone often fall short for tasks requiring temporal context, as they primarily focus on spatial information. To this end, researchers proposed a CNN-LSTM model that captures temporal dependencies across video frames [15]. Meanwhile, studies conducted by Sultani et al. and Ionescu et al. have presented evidence that combining CNNs with RNNs leads to significantly better results in anomaly detection since these methods allow for the learning of spatial and temporal representations [16]. Recent research has demonstrated the advantages of LSTM and GRU in capturing temporal dependencies, especially in traffic flow prediction tasks with noise [17]. Additionally, several studies have investigated human movement recognition using both supervised and zero-shot learning methods [18,19]. Previous research has explored CNN-based models for emotion recognition, primarily emphasizing spatial feature extraction. More recently, Vision Transformers (ViTs) have gained attention for their ability to capture global relationships. Additionally, Squeeze-and-Excitation (SE) blocks have proven effective in improving channel-wise feature representations. However, the integration of these architectures remains largely unexplored, particularly in the context of motion-based emotion datasets including the behavioural approach as well.

To provide a comprehensive overview of crowd behaviour analysis and the contributions of this study, the manuscript is structured as follows. Section 1 introduces the importance of anomaly detection in video surveillance specifically for crowd behaviour and emotion analysis, outlines key challenges in this domain, and identifies the research gap addressed in this study. Objective and reviews related work, focusing on the evolution of anomaly detection and crowd analysis techniques and their limitations. Methods section details the proposed method, HyViSE, along with the evaluation metrics used to assess its performance. Result section describes the experimental setup, including dataset characteristics and configurations. Discussion section presents the results, accompanied by an in-depth discussion and analysis, comparing findings with baseline models and alternative approaches. In last it concludes the manuscript by summarizing key contributions, discussing limitations, and suggesting future research directions in video anomaly detection in crowd analysis. Each section builds upon the previous one, ensuring a structured and coherent presentation of the study.

OBJECTIVES AND RELATED WORK

This section explores the use of Vision Transformers (ViTs) and Squeeze-and-Excitation (SE) blocks for crowd emotion and behavior analysis, along with Convolutional Neural Networks (CNNs), which have proven to be effective in anomaly detection by extracting spatial features from video frames. Deep neural network models perform effectively, particularly with small to medium-sized datasets. To enhance model accuracy and reliability, integrating multiple approaches has become essential in the current research landscape. Previous research has examined CNN-based models for emotion recognition, primarily emphasizing spatial feature extraction. More recently, Vision Transformers (ViTs) have gained attention for their ability to model global relationships. Additionally, Squeeze-and-Excitation (SE) blocks have proven effective in enhancing channel-wise feature representations. Vision transformers (ViTs) have emerged as a powerful tool in video anomaly detection, offering new perspectives and capabilities. Yuan et al. [23] showcased the effectiveness of integrating the "Video Vision Transformer" (ViViT) [24] with neural architectures like U-Net [25] to enhance anomaly detection performance. They have demonstrated notable advancements in processing complex video data, leading to improved accuracy in anomaly detection.

Recent studies have shown that integrating traditional machine learning techniques, such as decision trees and support vector machines, along with deep learning architectures like CNNs and RNNs [15] can greatly improve the performance of anomaly detection systems. An enhanced EfficientNet model was proposed by Luo et al.[20], optimized for 3D LiDAR data, achieving an impressive accuracy of 99.69%, while offering superior environmental robustness and lower invasiveness compared to conventional methods. The proposed architecture has limited analysis of performance under diverse environmental conditions and noise levels.

Choudhury and Badal [21] proposed lightweight CNN-LSTM applied on Inbuilt smartphone sensor-based dataset achieved 98% accuracy on six daily activities when raw sensor data was used directly in an uncontrolled environment against traditional models. This model worked with minimal preprocessing and optimized efficiency in computations. The proposed model is limited with no comparison with advanced deep learning models beyond conventional approaches.

Sai Ramesh et. al. [22] applied transfer learning with three different deep learning models on HAR dataset to reduce training time and computational costs. The proposed model has limitations, requiring substantial computational resources and access to large datasets for optimal performance. Lee and Kang [27] introduced AnoViT, a Vision Transformer-based encoder-decoder model designed to overcome the limitations of traditional convolutional encoder-decoders. The model enhances image anomaly detection and localization by capturing both local and global relationships within image patches. To address the issue of catastrophic forgetting in deep learning models, which leads to a significant decline in overall performance when new classes are incrementally introduced during training, Fan et al. [28, 29] developed a contrastive learning approach for Vision Transformers (ViTs). This method utilized ViT as a feature extractor and conducted image anomaly detection progressively within a contrastive learning framework. Park et al. [30] highlighted the importance of self-supervised learning in medical OOD detection, citing that it is especially challenging to generate anomalous images for rare diseases. To deal with the problem of not enough labeled data causing imprecise OOD detection, they used a self-supervised model known as UNETR. The UNETR model is a 3D version of the UNET, where its encoder uses a Vision Transformer (ViT) structure. Then they applied a skip-connection structure to connect the input images to the decoder after transforming them into sequence representations. Tahir and Anwar [26] investigated the use of Vision Transformers for pedestrian image retrieval and person re-identification in multi-camera systems, showcasing the effectiveness of integrating Vision Transformers with CNN models. The proposed research paper introduces a Transformer Spatiotemporal Attention Unsupervised Framework for enhancing video anomaly detection in large datasets. It addresses the limitations of traditional methods by leveraging transformers to model complex spatiotemporal relationships in video data. The framework utilizes a spatiotemporal attention mechanism to capture long-range dependencies across frames and regions, enabling effective anomaly detection without labeled data. Its unsupervised nature makes it scalable and cost-effective for real-world applications, such as surveillance and smart city monitoring. The approach demonstrates improved accuracy and robustness in detecting anomalies, particularly in dynamic and occluded environments. This innovation highlights the potential of transformers in advancing video analysis tasks [35]. Marwa Qaraqe et. al. [36]

introduced a deep learning model based on the swin transformer, which classifies crowd behavior into four categories: Natural (N), Large Peaceful Gathering (LPG), Large Violent Gathering (LVG), and Fighting. The proposed model integrates crowd-counting maps and optical flow maps to improve the detection of crowd dynamics and violence levels. The experimental analysis has shown that the incorporation of both crowd-counting and optical flow maps appreciably improves the accuracy of the model in detecting crowd behaviors.

To address the unbalanced distribution of information in video frames, Hu et al. [31] introduced a technique based on parallel spatial-temporal CNNs. They ensured overall representation of behavior without including extraneous data by applying a parallel 3D-CNN for an action over different time intervals. In addition, they applied an optical flow algorithm with a cell structure of varied size for spatial-temporal interest blocks with moving objects. To incorporate anomaly detection into IoT-based smart city projects, Kotkar and Sucharita [32] proposed "Modified Spatiotemporal Recurrent Neural Network using Long Short-Term Memory" (MST-RNN-LSTM). The innovation they used processed the normalized frame of the videos by generating cuboids for tracking motions. Discrete wavelet transforms combined with PCA were subsequently performed on those cuboids, followed by a process of training the features by means of the classification process within the RNN-LSTM model. Taghinezhad and Yazdi [33] proposed a video anomaly detection approach for surveillance systems, incorporating a memory module to retain the most relevant prototypical patterns of normal activities, thereby facilitating the detection of anomalies through false predictions for aberrant inputs. Their architecture, resembling a U-Net structure, utilized a Time-Distributed 2D encoder along with a 2D CNN-based decoder. Facial Expression Recognition (FER) has recently been a subject of interest due to the availability of multiple facial expression databases. However, the diversity of these databases introduces several challenges for facial recognition tasks, which are typically addressed using Convolutional Neural Networks (CNNs). Recently, Transformer models based on attention mechanisms have been introduced for vision tasks, offering a different approach from CNNs. One of the major disadvantages related to this model is that it needs a large training dataset, although FER databases are relatively limited compared to other vision applications. To address these limitations, we propose integrating a vision Transformer with a Squeeze-and-Excitation block for better FER performance. We evaluate our proposed method on publicly available FER databases that have CK+, JAFFE, RAF-DB, and SFEW datasets. Experimental results show that our model outperforms state-of-the-art methods on CK+ and SFEW while achieving competitive performance on JAFFE and RAF-DB [37]. Mario Alejandro Bravo-Ortiz et. al. [38] proposes a new spatial image steganalysis architecture called convolutional vision transformer architecture, CVTStego-Net, based on the integration of CNNs with Vision Transformers. This contributes to capturing the local and global dependencies that occur in images. To verify its proposed performance, CVTStego-Net is used on benchmark public datasets BOSSbase 1.01 and BOSSbase+Bows2 for superior classification accuracy across various steganographic algorithms. Experimental results show much better performance compared to the previous methods, reaching up to 93.80% accuracy at 0.4 bpp for WOW. It shows that using CNNs together with Vision Transformers can improve steganalysis significantly.

The summary of literature review is presented in Table 1. The field of video anomaly detection is advancing rapidly, particularly in detecting abnormal behavior within dense crowds, where it is of critical importance. Significant progress has been made using transformer-based and other advanced techniques, positioning these developments at the core of robust security systems aimed at enhancing public safety and security. Recent research highlights Vision Transformers as leading models for detecting video anomalies across various domains. However, there remains a high demand for intelligent surveillance systems to further strengthen public safety and security.

Table 1. Summary of Literature review

Study	Key Contribution	Methodology	Performance/Results	Limitations
Yuan et al. [23]	Integration of ViViT with U-Net for anomaly detection	Video Vision Transformer (ViViT) + U-Net	Improved accuracy in anomaly detection	Limited analysis under diverse environmental conditions

Luo et al. [20]	Enhanced EfficientNet for 3D LiDAR data	EfficientNet optimized for 3D LiDAR	99.69% accuracy, superior environmental robustness	Limited performance analysis under noise levels
Choudhury and Badal [21]	Lightweight CNN-LSTM for smartphone sensor data	CNN-LSTM on raw sensor data	98% accuracy for six daily activities	No comparison with advanced deep learning models
Sai Ramesh et al. [22]	Transfer learning for HAR dataset	Three deep learning models with transfer learning	Reduced training time and computational costs	Requires substantial computational resources and large datasets
Tahir and Anwar [26]	Vision Transformers for pedestrian image retrieval	Vision Transformers + CNNs	Effective for person re-identification	-
Lee and Kang [27]	AnoViT for image anomaly detection	Vision Transformer-based encoder-decoder	Enhanced anomaly detection and localization	-
Fan et al. [28,29]	Contrastive learning for Vision Transformers	ViT as feature extractor + contrastive learning framework	Addresses catastrophic forgetting in incremental learning	-
Park et al. [30]	Self-supervised learning for medical OOD detection	UNETR (3D UNET with ViT encoder)	Effective for rare disease detection	Challenges in generating anomalous images for rare diseases
Proposed Transformer Framework [35]	Transformer Spatiotemporal Attention for video anomaly detection	Spatiotemporal attention mechanism	Improved accuracy and robustness in dynamic environments	Unsupervised nature may limit precision in labeled data scenarios
Marwa Qaraqe et al. [36]	Swin Transformer for crowd behavior classification	Swin Transformer + crowd-counting and optical flow maps	Improved accuracy in detecting crowd dynamics and violence	-
Hu et al. [31]	Parallel spatial-temporal CNNs for video frames	Parallel 3D-CNN + optical flow algorithm	Balanced representation of behavior	-
Kotkar and Sucharita [32]	MST-RNN-LSTM for IoT-based smart city projects	MST-RNN-LSTM + discrete wavelet transforms + PCA	Effective motion tracking and anomaly detection	-

Taghinezhad and Yazdi [33]	Memory module for video anomaly detection	U-Net-like architecture with Time-Distributed 2D encoder + 2D CNN decoder	Retains prototypical patterns for anomaly detection	-
Proposed FER Model [37]	Vision Transformer + SE block for Facial Expression Recognition (FER)	ViT + Squeeze-and-Excitation block	Outperforms state-of-the-art on CK+ and SFEW; competitive on JAFFE and RAF-DB	Requires large training datasets; FER databases are limited
Bravo-Ortiz et al. [38]	CVTStego-Net for spatial image steganalysis	CNN + Vision Transformer integration	93.80% accuracy at 0.4 bpp for WOW steganographic algorithm	-

METHODS

Vision Transformers (ViTs), originally developed by Vaswani et al. in 2017 for natural language processing and later adapted for image tasks, divide an image into fixed-size patches. These patches are linearly embedded into a high-dimensional space and processed by a transformer architecture with multi-head self-attention layers and feed-forward networks. ViTs excel in capturing global context and long-range dependencies, essential for analyzing complex image patterns. They also support flexible input representations, accommodating varying sizes and resolutions, and are highly scalable, enabling state-of-the-art performance with large datasets and computational resources [34]. CNNs have found great utility in solving image classification tasks and excel on object identification due to the presence of potential local patterns, edges, and texture. These networks are designed especially for the purpose of spatial hierarchies and significant local features within images. This is achieved by using convolutional layers that focus on extracting local features and pooling layers that down sample feature maps while preserving essential details despite the reduction in spatial dimensions as shown in Fig. 1. However, traditional CNNs suffer from a lack of scalability with increasing image size and dataset complexity. Their fixed-size receptive fields and restricted attention mechanisms hinder their ability to model long-range dependencies effectively.

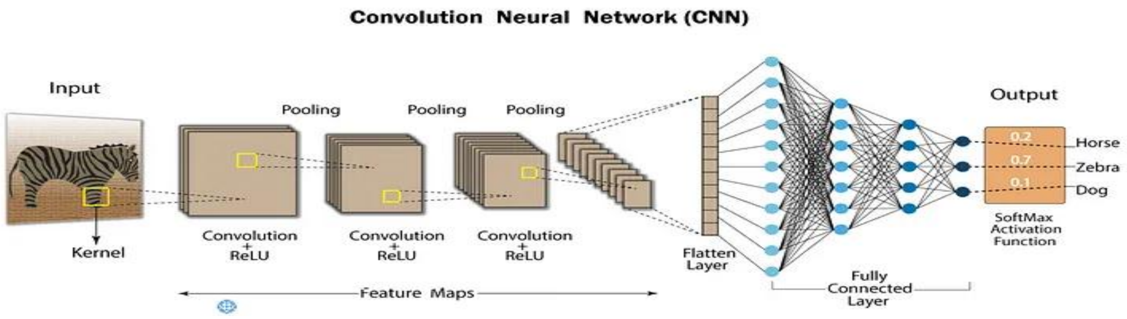

Fig. 1 CNN for Image Classification [39]

The ViT (Vision Transformer) have recently attracted interest due to their capacity to record semantic information and long-range relationships in pictures. Transformers have demonstrated outstanding performance in natural language processing tasks. In case of image classification such exception achievement is achieved by replacing traditional convolutional layers with self-attention mechanisms, allowing the model to capture long-range dependencies and contextual relationships more effectively [39]. Vision Transformers are highly effective at processing images as per Fig. 2, because they rely on self-attention mechanisms instead of rigid spatial hierarchies. This flexibility enables them to focus on key regions of an image, even if those regions are far apart, and to identify relationships between distant pixels. As a result, Vision Transformers have proven to be particularly strong in tasks like image captioning, image classification and image generation, where a deep understanding of the entire image's content is essential.

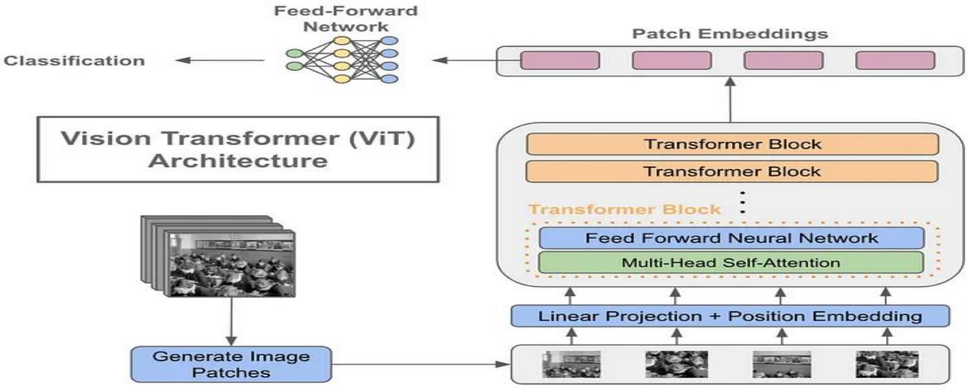
Feed-Forward Network
Classification
Patch Embeddings
Vision Transformer (ViT) Architecture
Transformer Block
Transformer Block
Transformer Block
Feed Forward Neural Network
Multi-Head Self-Attention
Linear Projection + Position Embedding
Generate Image Patches

Fig. 2 Vision Transformer [39]

Fusion of CNN, ViT and SE (Squeeze-and-Excitation) block (HyViSE)

Researchers have explored hybrid models that integrate CNNs and Vision Transformers to leverage the strengths of both architectures. By using a CNN as the foundation, the model can incorporate the attention mechanisms of Vision Transformers to enhance its understanding of the global context. This combination allows for the fast local feature extraction of CNNs while benefiting from the precise global dependency representation of Vision Transformers. The Hybrid Vision Transformer (HVT) is a well-known example of a hybrid architecture that combines a convolutional neural network (CNN) with a Vision Transformer. Built on a CNN backbone, it integrates a Vision Transformer module to enhance global context and dependency capture by analyzing the feature maps produced by the CNN. This synergy has led to state-of-the-art performance across various image classification benchmarks. Convolutional Neural Networks (CNNs) specialize in capturing local features, while Vision Transformers (ViTs) are adept at learning global features. CNNs achieve this by utilizing convolutional layers to extract patterns specific to small regions of the input image. In contrast, Vision Transformers leverage self-attention mechanisms, enabling them to capture broader, more global characteristics across the entire image. Squeeze-and-Excitation (SE) is a mechanism developed to enhance the representational capacity of neural networks, especially within Convolutional Neural Networks (CNNs). Originally proposed in the 2018 paper "Squeeze-and-Excitation Networks" [40] by Jie Hu, Li Shen, and Gang Sun, its primary objective is to adaptively recalibrate feature responses across channels. By enabling the network to emphasize the most relevant features, SE significantly boosts performance in tasks like image classification, object detection, and segmentation. The fundamental concept of SE is straightforward: first, "squeeze" the spatial dimensions (height and width) of feature maps to create a global descriptor, and then "excite" the channels to dynamically recalibrate their significance.

The first step for the SE block is to obtain a global feature vector by squeezing the feature map's height and width. This is usually done using global average pooling (GAP). For a given input feature map with size H × W × C (where H is the height, W is the width, and C is the number of channels), global average pooling computes the mean of each channel across all spatial positions:

$$z_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} x_{ijc} \quad (1)$$

Here, z_c is the global descriptor for channel c, and x_{ijc} is the feature at position (i,j) in the c-th channel. The result of this operation is a vector $z \in R^C$, where each element of the vector represents a summary of a specific channel's spatial information. Once we have the global descriptors for each channel, the next step is to excite or recalibrate the channels. This is done by passing the vector z through a small neural network, typically consisting of two fully connected (FC) layers. The first fully connected (FC) layer reduces the dimensionality of z (using a reduction ratio r) to generate a more compact representation. The second FC layer then restores the dimensionality back to C, assigning a weight to each channel. These weights are passed through a sigmoid activation function, ensuring they fall within the range [0,1].

$$s = \sigma\left(W_2 \delta(W1z)\right) \qquad (2)$$

W1 and W2 weight matrices in the fully connected layers, δ is a ReLU activation function (applied after the first FC layer). σ is the sigmoid activation function applied at the end to produce the final channel-wise attention weights. The output $s \in R^C$ is a vector of channel attention weights, where each element corresponds to the importance of the corresponding channel. Finally, the attention weights s are used to recalibrate the input feature map. Each channel ccc of the input feature map is multiplied by its corresponding attention weight s_c

$$\hat{x}_c = x_c \,.\, s_c \qquad (3)$$

This process enhances the important channels and suppresses the less important ones. The recalibrated feature map $\hat{X}$ is then passed on to the next layers of the network. In CNNs (such as ResNet and Inception), squeeze-and-excitation has been demonstrated to enhance performance. It can also be used in other architectures, such as Vision Transformers (ViTs), where it enables the model to adaptively focus on the most crucial characteristics across patches. SE applies channel-wise attention, enhancing important features while suppressing less relevant ones which helps the model focus on the most discriminative spatial and channel-based features and improved generalization to unseen data. With SE Block CNN provides high-quality refined embedding before passing them to the Transformer blocks, leading to better token representations. The proposed architecture/model is shown in fig. 3.

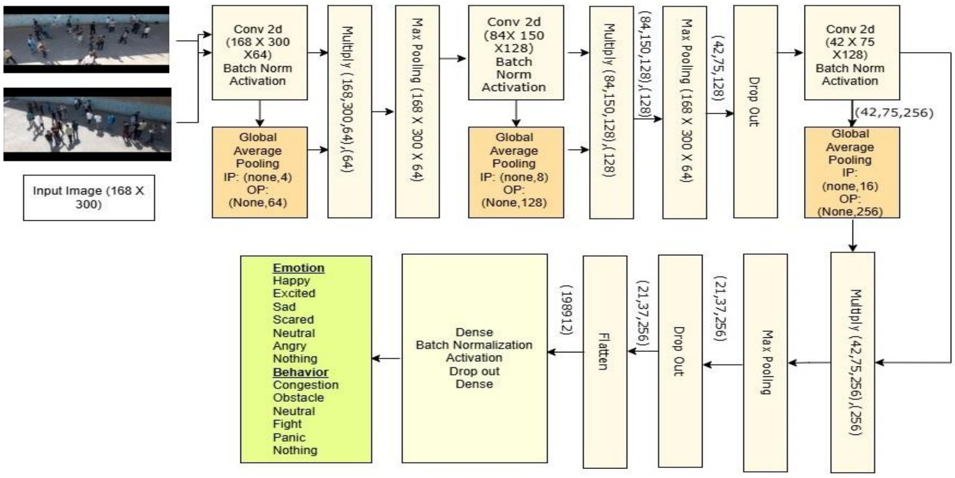
Input Image (168 X 300)
Conv 2d (168 X 300 X64) Batch Norm Activation
Global Average Pooling IP: (none,4) OP: (None,64)
Multiply (168,300,64),(64)
Max Pooling (168 X 300 X 64)
Conv 2d (84X 150 X128) Batch Norm Activation
Global Average Pooling IP: (none,8) OP: (None,128)
Multiply (84,150,128),(128)
(84,150,128),(128)
Max Pooling (168 X 300 X 64)
(42,75,128)
Drop Out
Conv 2d (42 X 75 X128) Batch Norm Activation
(42,75,256)
Global Average Pooling IP: (none,16) OP: (None,256)
Multiply (42,75,256),(256)
Max Pooling
(21,37,256)
Drop Out
(21,37,256)
Flatten
(198912)
Dense
Batch Normalization
Activation
Drop out
Dense
Emotion
Happy
Excited
Sad
Scared
Neutral
Angry
Nothing
Behavior
Congestion
Obstacle
Neutral
Fight
Panic
Nothing

Fig. 3 Proposed HyViSE Architecture

Motion Emotion Dataset (MED)

Most previous research has focused on identifying abnormalities in video sequences, ultimately sorting events into two categories: normal and abnormal. However, there has been a scarcity of studies aimed at uncovering the emotional and behavioral characteristics of crowds. The current leading train and test datasets generally classify images or videos into normal and abnormal categories. To enhance our understanding of crowd dynamics, these datasets should be more detailed by including labels for emotions such as sadness, crying, and happiness, as well as behaviors like congestion, normalcy, panic, and violent/non-violent actions. For instance, datasets like UCSD Anomaly Detection, UCF Crowd 50, and Violent Flow (which categorizes violent actions into Violent and Non-Violent) should incorporate these additional behavioral labels to provide greater insight into crowd situations.

The objective of this research is to classify the crowd according to its emotion and behaviour related characteristics. The Motion Emotion Dataset (MED) was published in 2016 Rabbiee et al. [41], which is an extensive collection created to capture the subtleties of human emotions through movement and behavior. MED includes a diverse range of scenarios, featuring both individual and group interactions, to capture the intricacies of emotional expression in social dynamics. This variety provides researchers with the opportunity to develop and evaluate emotion recognition models in real-world contexts, enhancing insights into human-computer interaction and emotional comprehension.

Preprocessing of Dataset

The MED dataset is publicly available from Github (https://github.com/hosseinm/med). The dataset includes 31 distinct videos with an approximate length of 60 to 120 seconds having frame size 480 (Height) X 854 (Width) and frame rate : 30 fmps. Additionally, the dataset provides frame-by-frame annotations for various emotion and behavior-related labels in a MATLAB (.m) file, with the annotation numbers and class names and number of images per class is listed in Table 2. The images are divided into the train and train folder and the sample images of the crowd's emotion and behavior dataset. As per the annotation provided by the provided dataset is prepared.

Table 2 Sample images of various class

Emotion				Behaviour			
Happy 1991				Congestion 2379			
Excited 3802				Obstacle 6380			
Sad 1155				Neutral 26029			
Scared 2167				Fight 4469			
Neutral 25476				Panic 1991			
Angry 5752				Nothing 4040			
Nothing 3974				–	–	–	–

Explanation of the Proposed Architecture

This model combines three powerful deep learning components:

1. Convolutional Neural Network (CNN) – Extracts spatial features.
2. Vision Transformer (ViT) – Captures global dependencies using self-attention.
3. Squeeze-and-Excitation (SE) Blocks – Enhances channel-wise feature representation.

1. Convolutional Neural Network (CNN) : The CNN layers extract local features from the input image. The convolutional layer applies a set of learnable filters to the input. After applying the convolution operation, you get an output feature map, which will have a size reduced from the original input depending on the filter size and the stride used.

$$X'_{i,j,c} = \sum_{m=0}^{K-1} \sum_{n=0}^{K-1} \sum_{d=0}^{C_{in}-1} W_{m,n,d,c} \cdot X_{i+m,j+n,d+b_c} \qquad (4)$$

where, X is input feature map of size H × W × C_{in}

W is the convolutional kernel of size $K \times K \times C_{in} \times C_{out}$.

b_c is the bias for the c-th output channel.

X' is the output feature map of size $H' \times W' \times C_{out}$

To stabilize training, batch normalization normalizes activations is applied

$$\hat{x} = x - \mu$$

$$———— \qquad (5)$$

$$\sigma$$

$$y = \gamma\hat{x} + \beta \qquad (6)$$

where, μ and σ are the batch mean and standard deviation. γ and β are learnable parameters.

After convolution, an activation function is applied to introduce non-linearity into the model. The **ReLU** (Rectified Linear Unit) function is commonly used in CNNs. x is the input to the activation function (the output of the convolution). ReLU sets all negative values to 0, while leaving positive values unchanged.

$$f(x) = \max(0, x) \qquad (7)$$

Downsampling is performed using max-pooling, which is used to reduce the spatial dimensions of the feature map (downsampling) while retaining the most important information. For a region of the feature map of size 2×22 \times 22×2, the pooling operation computes the maximum value in that region

$$X'_{i,j,c} = \max_{(m,n)\epsilon R} X_{i+m,j+n,c} \qquad (8)$$

where R is the pulling window. The SE block adaptively recalibrates channel-wise feature maps. Each feature channel is aggregated using Global Average Pooling (squeeze) as per the eq. (1).

The excitation (fully connected layer and scaling) applied to two dense layers as per the eq. (2).

The Vision Transformer (ViT) block models long-range dependencies using multi-head self-attention (MHSA) and feed-forward networks (FFN), Residual Connections & Layer Normalization to identify the long range dependencies. Initially Multi head self attention (MHSA) applied to each patch embedding that results in self-attention. The input to the MHSA is the sequence of patch embeddings (including the class token) after adding positional embeddings and then after the residual connection and layer normalization. This completes the Transformer encoder layer.

$$Q=XW_Q \ , K=XW_K \ , \ V=XW_V$$

$$\text{Attention}(Q \ , K \ , V) = \text{softmax}\left(QK^T/\sqrt{d_k}\right)V \qquad (9)$$

where, W_Q, W_K, W_V are projection metrices and d_k is the key dimension. For multiple heads,

$$\text{MHSA}(X) = \text{Concat}\ (\text{head}_1, \ldots., \text{head}_h)\ W_O \qquad (10)$$

W_O is an output projection matrix.

Residual connections:

$$X' = \text{LayerNorm}(X + \text{MHSA}(X))$$

$$X'' = \text{LayerNorm}\ (X' + \text{FFN}\ (X')) \qquad (11)$$

After ViT processing we are obtaining Global representation by applying Global Average Pooling, Dense Layer and Softmax.

Global Average Pooling : $X' = \frac{1}{N} \sum_{i=1}^{N} X_i$

Dense Layers & Softmax Output: logits = $W \cdot X' + b$

$$\widehat{y_i} = \frac{e^{\mathrm{logits}_i}}{\sum_{j=1}^{C} e^{\mathrm{logits}_i}} \tag{12}$$

C is the number of classes, in case of Emotion Dataset 7 and for Behavior dataset 6.

This hybrid model leverages both CNN’s local understanding and ViT’s global attention, enhancing performance for image classification.

RESULTS

The proposed model is applied to both the Emotion and Behavior MED datasets. The experiments are conducted on a Dell POWEREDGE R740 server, equipped with an NVIDIA Tesla V100 32GB Passive GPU, dual Intel Xeon Gold 5118 processors (2.3GHz), and four 32GB RDIMM 2666MT/s Dual Rank RAM modules. Additionally, the same model is run on Google Colab using a T100 GPU to measure the execution time. During the implementation, the following hyperparameters were utilized to ensure optimal performance: Epochs = 10, Learning Rate = 0.0001, Batch Size = 16, Kernel Size = 3x3, and the Adam optimizer. Additionally, the dataset was divided into an 80-20 split for training and testing purposes, respectively. After the model compilation, the model was able to identify a total 51,308,387 parameters, out of which, 51,306,979 are trainable parameters and 1,408 non-trainable parameters for the MED emotion dataset. The execution time was comparatively less in Google Colab with T100 GPU than Dell Poweredge R740 in house server. After 10 epochs, the proposed model achieved a test accuracy of 99.18% with a test loss of 1.92%, along with a validation accuracy of 99.21% and a validation loss of 3.27%. Fig. 4 shows the graph for accuracy and loss per epoch of training and validation. To validate the proposed model, Confusion Matrix is prepared which shows in Fig. 5. As per Fig. 5 almost all classes are properly classified and very few classes show the miss classification.

The proposed model is applied for the behaviour dataset of Motion Emotion Dataset. The model is executed on Google Colab using T100 GPU. During the implementation, the following hyperparameters were utilized to ensure optimal performance: Epochs = 10, Learning Rate = 0.0001, Batch Size = 16, Kernel Size = 3x3, and the Adam optimizer. Additionally, the dataset was divided into an 80-20 split for training and testing purposes, respectively. After the model compilation, the model was able to identify a total 51,308,130 parameters, out of which, 51,306,722 are trainable parameters and 1,408 non-trainable parameters for the MED behavior dataset. After 10 epochs, the proposed model achieved a test accuracy of 97.02% with a test loss of 4.92%, along with a validation accuracy of 97.08% and a validation loss of 6.42%. Fig. 6 shows the graph for accuracy and loss per epoch of training and validation. To validate the proposed model, Confusion Matrix is prepared which shows in Fig. 7. As per Fig. 7 almost all classes are properly classified and very few classes show the miss classification.

Experiment Result Comparison and Discussion

The results are compared with state-of-the-art models using various crowd anomaly detection datasets. Crowd Anomaly Detection (CAD) has become an emerging topic in the era of automation, where it enables the detection of potential large-scale incidents within a specific time frame, allowing for timely countermeasures to minimize casualties. In concern to this, an efficient AI model is required, which can identify the abnormality during the live streaming.As shown in Table 4, research papers that have proposed hybrid approaches combining CNN and ViT, or other methods, applied to benchmark datasets such as UCSD Ped1, Shanghai Tech, UCF Crime, Avenue, Chuke Avenue, UCSC Ped2, and the Motion Emotion Dataset (MED), along with their result efficiency/accuracy, are provided.

Journal of Information Systems Engineering and Management
2024, 9(4s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

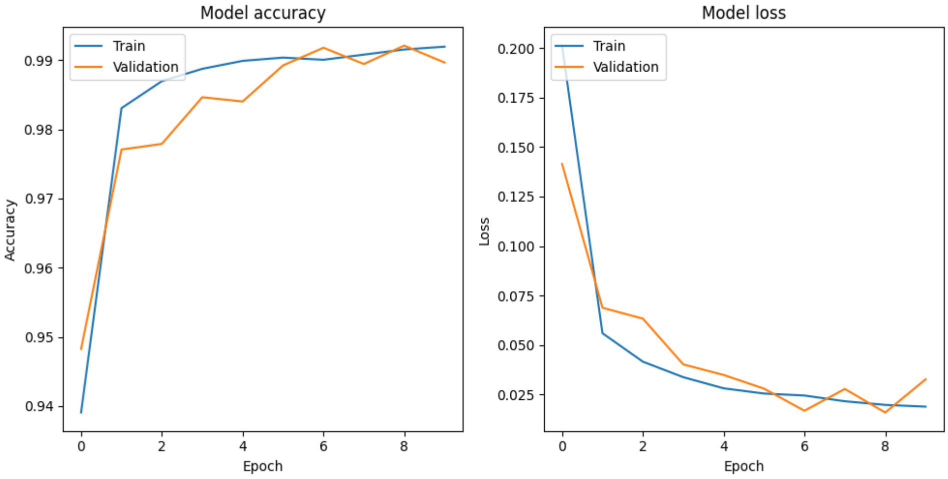

Fig. 4 Model Accuracy graph for Emotion Dataset

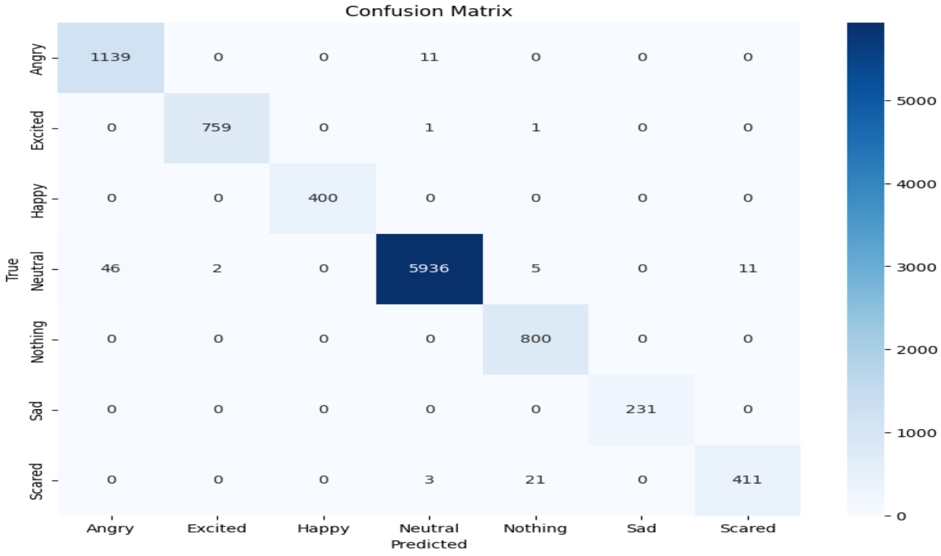

Fig. 5 Confusion Matrix for Emotion Dataset

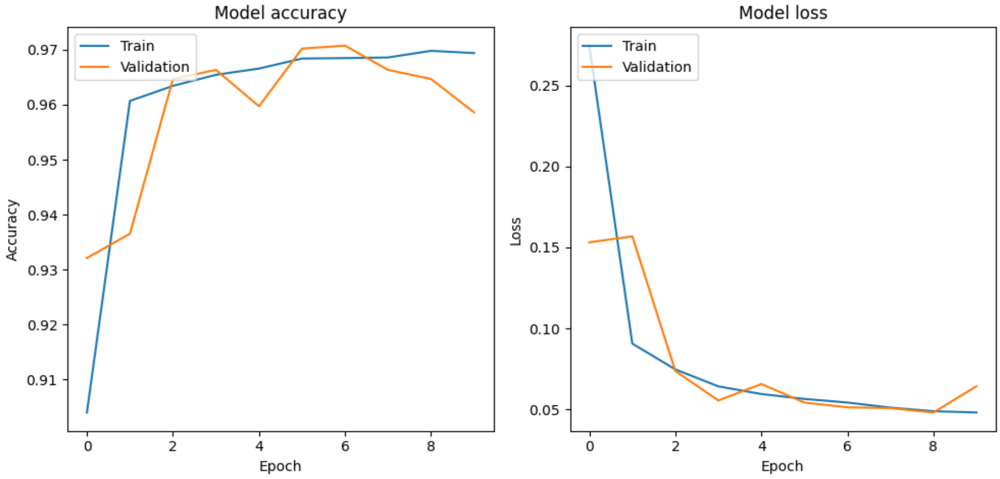

Fig. 6 Model Accuracy graph for Behaviour Dataset

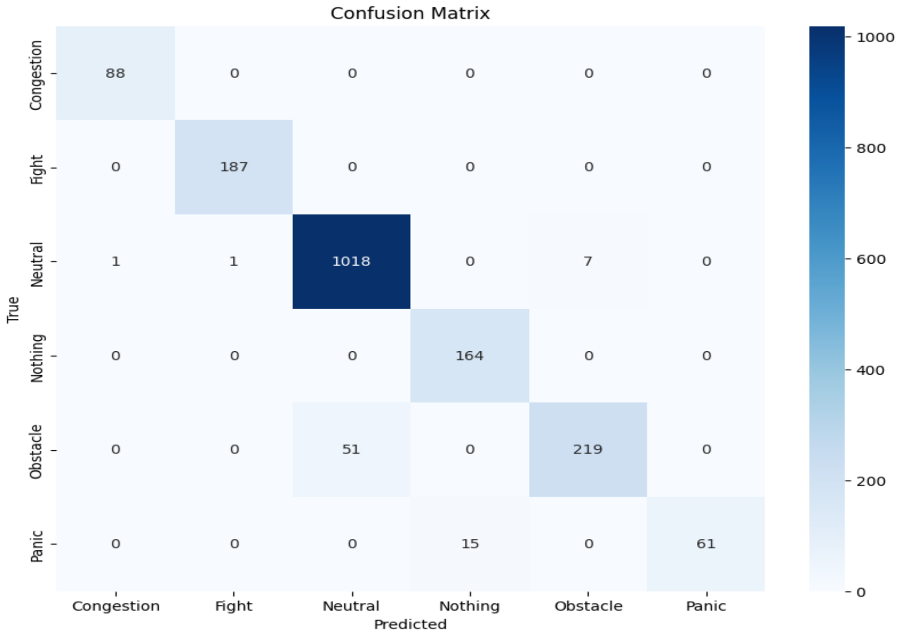

Fig. 7 Confusion Matrix for Behaviour Dataset

Table 3 Result comparison with other approaches

Paper Title	Model Used	Dataset	Accuracy/ Result	Year
Vision Transformers for Crowd Anomaly Detection [42]	Vision Transformer (ViT)	ShanghaiTech	94.70%	2021
Hybrid CNN-Transformer for Crowd Anomaly Detection [43]	CNN + Vision Transformer	UCF-Crime	**95.10%**	2022
Transformers for Anomaly Detection in Crowded Environments [44]	Vision Transformer (ViT)	CUHK Avenue	93.80%	2021
Vision Transformers in Surveillance: Crowd Anomaly Detection [45]	Vision Transformer (ViT)	UCF-Crime	94.20%	2022
Crowd Anomaly Detection using Multi-Stream CNNs [46]	CNN	ShanghaiTech	90.80%	2020
Efficient Crowd Anomaly Detection using Vision Transformers [47]	Vision Transformer (ViT)	UCSD Ped2	93.50%	2021
A Comparative Study of CNN and Transformers for Crowd Anomaly Detection [48]	CNN + Vision Transformer	CUHK Avenue	**94.90%**	2022
Spatio-Temporal Autoencoders for	Spatio-Temporal	Motion Emotion	88.60%	2020

Crowd Anomaly Detection [49]	Autoencoder			
Graph Convolutional Networks for Crowd Anomaly Detection [50]	Graph Convolutional Network (GCN)	Motion Emotion	89.30%	2021
Motion-Aware Transformers for Crowd Anomaly Detection [51]	Motion-Aware Transformer	Motion Emotion	**91.50%**	2022
Crowd Anomaly Detection using Optical Flow and CNN [52]	CNN + Optical Flow	Motion Emotion	87.90%	2019
Multi-Modal Fusion for Crowd Anomaly Detection [53]	CNN + LSTM	Motion Emotion	90.10%	2021
Proposed Approach	**CNN + ViT +SE**	**Motion Emotion**	**99.21**	**2025**

Table 3 presents various hybrid approaches applied to different datasets. According to [48], the CNN and ViT hybrid approach achieved an accuracy of 94.90%, while a similar approach achieved 95.10% accuracy on the UCF-Crime dataset. For the Motion Emotion Dataset, the Motion-Aware Transformer approach, as described in [51], achieved an accuracy of 91.50%.

DISCUSSION

Crowd anomaly detection has always posed a significant challenge due to issues related to dataset availability, classification, and noise in the images. Various deep learning approaches have been applied to public datasets to identify abnormalities in crowds. However, the classification of publicly available datasets is typically limited to detecting only normal and abnormal crowds. Very few datasets offer multiple classes, which could help in understanding the emotional and behavioral context of the crowd. The Motion Emotion Dataset (MED) is an efficient dataset that can address this gap.

In this work, we propose a hybrid approach that combines CNN, ViT, and the SE block to classify different crowd behaviors, such as Congestion, Obstacle, Neutral, Fight, Panic, Nothing, and emotions like Happy, Excited, Sad, Scared, Neutral, Angry, and Nothing. The proposed model achieved 99.21% accuracy for emotion dataset classification and 97.08% for behavior dataset classification, demonstrating the effectiveness of integrating attention mechanisms like SE for enhanced feature calibration in detecting anomalies.

While the use of Squeeze-and-Excitation (SE) in the proposed approach has shown promising results, future research could explore other attention mechanisms or adaptive attention methods to better capture diverse crowd behaviors and emotions. To further generalize the model, future work could focus on applying it to additional datasets and fine-tuning the approach. Furthermore, optimization efforts for large-scale, real-time crowd monitoring systems could be a valuable direction for future advancements.

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