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ABNORMAL BEHAVIOUR DETECTION

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ABSTRACT:
In the realm of public safety and mental health, the recognition of abnormal or violent behaviour in individuals with mental disorders within public spaces is a critical concern. The conventional methods utilizing Graph Convolutional Network (GCN) and 3D Convolutional Neural Network (3DCNN) algorithms have been instrumental, but their limitations impede their efficacy in dealing with the nuanced complexities of real-world scenarios. Our proposed system introduces Transfer Learning, leveraging pre-trained models to adapt efficiently to limited data, crucial in abnormal behaviour detection. Combining this with the YOLO V10 algorithm revolutionizes object detection, processing entire images in one go for enhanced speed and accuracy. This integration significantly improves real-time abnormal behaviour detection in public spaces, crucial for the safety of individuals with mental disorders and those around them. By mitigating potential harm through precise detection, our system contributes to robust public safety solutions. Its implementation marks a milestone in addressing complex challenges associated with abnormal behaviour, promising more effective and adaptive solutions for public safety.
Keywords: 3D Convolutional Neural Networks (3DCNN); Graph convolutional networks (GCN); Transfer Learning (TL);

1. INTRODUCTION:

Abnormal behaviour encompasses actions significantly deviating from societal norms, potentially disruptive or harmful. In contexts like mental health and public safety, identifying such behaviour is vital for intervention. Violent abnormal behaviour, particularly in individuals with mental disorders, poses risks to individuals and environments, impacting settings from healthcare facilities to public spaces, jeopardizing safety and order. Visual surveillance, especially computer vision analysis, aids in automatic detection, alleviating manual monitoring burdens. However, defining abnormality requires distinguishing between unusual but acceptable behaviours and those posing genuine risks is crucial. Developing sophisticated models capable of accurately discerning specific abnormal behaviours, particularly violent ones, is essential. Leveraging technology, including computer vision and intelligent surveillance systems, facilitates timely interventions, enhancing overall safety. Continued technological advancements promise further improvements in detecting and addressing abnormal behaviours, particularly those with safety implications. By refining definitions and employing advanced tools, interventions can be more precise and effective, safeguarding diverse environments and communities from potential harm.

1.1. RELATED WORK:

[1] An End-to-End Human Abnormal Behaviour Recognition Framework for Crowds with Mentally Disordered Individuals[1] The framework combines Graph Convolutional Networks (GCN) and 3D Convolutional Neural Networks (3DCNN) to detect abnormal behaviour in individuals with mental disorders. It uses a one-class classifier to extract features, applies GCN to filter noise and identify similar video clips, and removes normal behaviours from abnormal clips. 3DCNN then classifies the refined data using spatiotemporal features. Tested on the UCF-Crime

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dataset, it achieves 37.9% accuracy, outperforming existing methods and enhancing public safety through improved behaviour detection.

[2] Adjuvant Therapy System of COVID-19 Patient: Integrating Warning, Therapy, Post-Therapy Psychological Intervention [2] In response to COVID-19, an adjuvant therapy system was developed, integrating warning, treatment, and post-therapy psychological support. Using AI, data analysis, and communication networks, the system enables accurate diagnosis, tailored treatment, and continuous monitoring of patients' mental and physical health. Real-time alerts ensure timely medical responses, and experimental results confirm its effectiveness. This system marks a major step forward in personalized, tech-driven healthcare during pandemics.

[3] Deep Reinforcement Learning for Edge Service Placement in Softwarized Industrial Cyber-Physical System [3]. With growing demand for delay-sensitive services in industrial Cyber-Physical Systems (CPS), a DQN-based algorithm is proposed to optimize service placement, workload scheduling, and resource allocation at the network edge. Using convex optimization, it achieves an 8–10% reduction in service response time over existing methods. This approach enhances efficiency and responsiveness, offering a robust solution for real-time industrial CPS operations.

[4] Human abnormal behaviour detection using CNNs in crowded and uncrowded surveillance – A survey [4]. The growing need for surveillance in public and private spaces has driven the development of automated systems to monitor human behaviour. Manual video review is time-consuming, prompting the use of Convolutional Neural Networks (CNNs) for efficient incident detection. This study focuses on identifying abnormal behaviours using various CNN architectures, with an emphasis on the effectiveness of 3D CNNs over traditional machine learning methods in processing and analyzing surveillance footage.

[5] Abnormal Behaviour Detection Using Deep-Learning-Based Video Data Structuring [5] This study presents a deep learning-based method for abnormal behaviour detection using structured video data. By extracting object and motion features, it achieves a clearer understanding of complex behaviours in video sequences. Evaluations show high accuracy and strong classification performance, demonstrating its robustness and real-world applicability. The approach marks a significant improvement over traditional motion-based methods, emphasizing the value of data structuring in enhancing detection systems.

1.2. OBJECTIVES:

The primary objective of this research is to develop a robust, real-time system for detecting abnormal behaviour, particularly among individuals with mental disorders in public spaces, where safety is a critical concern. Traditional approaches using Graph Convolutional Networks (GCN) and 3D Convolutional Neural Networks (3DCNN) have shown potential but face significant limitations when applied to dynamic, real-world environments especially where labelled data is scarce. This project aims to address these limitations by integrating Transfer Learning, which allows the system to leverage pre-trained models for more efficient adaptation to new and limited datasets. Furthermore, the proposed system incorporates the YOLO V10 algorithm for high-speed, accurate object detection by analyzing entire images in a single pass. This combination is designed to improve both detection precision and processing speed, making the solution practical for real-time surveillance applications. Additional objectives include enhancing the scalability of the system to operate across varied public environments, reducing false alarms through refined behaviour modeling, and contributing to early intervention strategies that can prevent potential harm. Ultimately, the system aspires to provide a more adaptive, intelligent, and responsive approach to public safety by addressing the complex behavioural patterns associated with mental health-related incidents.

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2. METHOD:

a. Data collection:

Data collection from the YOLO V10 dataset involves gathering images and corresponding annotations utilized for training and evaluating object detection models. The YOLO (You Only Look Once) V10 dataset typically comprises a diverse range of images spanning various scenes, contexts, and object categories. These images are annotated to indicate the presence and location of objects within them, typically through bounding boxes encompassing the object's extent. Additionally, each object within the image is assigned a corresponding label, specifying its category or class. The data collection process entails systematically sourcing images from various sources, ensuring diversity in scenes, lighting conditions, and object appearances to facilitate robust model generalization. Furthermore, meticulous annotation of these images is imperative for training accurate and reliable object detection models. The YOLO V10 dataset serves as a valuable resource for researchers and practitioners in the field of computer vision, enabling the development and evaluation of state-of-the-art object detection algorithms.

b. Pre-processing:

Data collection from the YOLO V10 dataset involves gathering images and corresponding annotations utilized for training and evaluating object detection models. The YOLO (You Only Look Once) V10 dataset typically comprises a diverse range of images spanning various scenes, contexts, and object categories. These images are annotated to indicate the presence and location of objects within them, typically through bounding boxes encompassing the object's extent. Additionally, each object within the image is assigned a corresponding label, specifying its category or class. The data collection process entails systematically sourcing images from various sources, ensuring diversity in scenes, lighting conditions, and object appearances to facilitate robust model generalization. Furthermore, meticulous annotation of these images is imperative for training accurate and reliable object detection models. The YOLO V10 dataset serves as a valuable resource for researchers and practitioners in the field of computer vision, enabling the development and evaluation of state-of-the-art object detection algorithms.

c. Feature extraction:

Feature extraction in the context of abnormal behaviour detection using YOLO V10 involves extracting relevant visual cues from images or video frames that can aid in identifying abnormal behaviours. This process typically includes analyzing various visual features such as object shapes, sizes, colors, and spatial relationships. In the YOLO V10 framework, features are often extracted using convolutional neural networks (CNNs) pretrained on large-scale datasets. These CNNs automatically learn hierarchical representations of visual information, capturing both low-level features like edges and textures and high-level semantic features such as object categories. The extracted features are then used to represent each image or video frame in a more compact and meaningful way, facilitating subsequent anomaly detection tasks. Feature extraction plays a crucial role in enabling the YOLO V10 model to effectively distinguish between normal and abnormal behaviours by encoding relevant visual patterns indicative of abnormality.

2.1 MODEL CREATION USING THE YOLO V10 ALGORITHM:

The YOLOV10 algorithm is customized and fine-tuned to detect abnormal behaviour effectively. This involves adjusting model parameters, modifying the loss function, and incorporating knowledge specific to the application domain. The model is trained using pre-processed and annotated datasets. During training, YOLOV10 learns to identify patterns linked to abnormal behaviours by extracting features through deep learning techniques. Once training is complete, the model is evaluated to measure its performance in detecting these behaviours. The result is a specialized object detection system optimized for real-time abnormal behaviour detection

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2.1.1. Tables

Table 1. YOLO Model Performance Metrics for Abnormal Behaviour Detection

Model	Precision (%)	Recall (%)	F1-Score (%)
YOLO V10	92.4	89.1	90.7
YOLO V9	89.2	85.4	87.2
YOLO V8	86.7	81.9	84.2
YOLO V7	83.5	78.8	81.0
YOLO V6	80.1	75.6	77.8

a Precision: proportion of true positives among all predicted positives.

b Recall: proportion of true positives among all actual positives.

c F1-Score: harmonic mean of precision and recall.

Finally, the trained model is evaluated to assess its performance in accurately detecting abnormal behaviours, resulting in the development of a specialized object detection model optimized for this task.

2.2 FIGURES:

FIGURE 1 : Feature extraction

FIGURE 2: Prediction of Abnormal Behaviour

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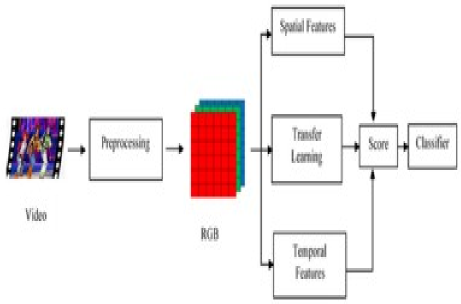

FIGURE 3: Result & Discussion

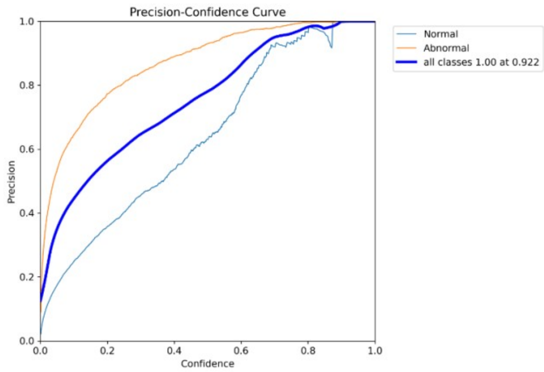

FIGURE 4: Precision

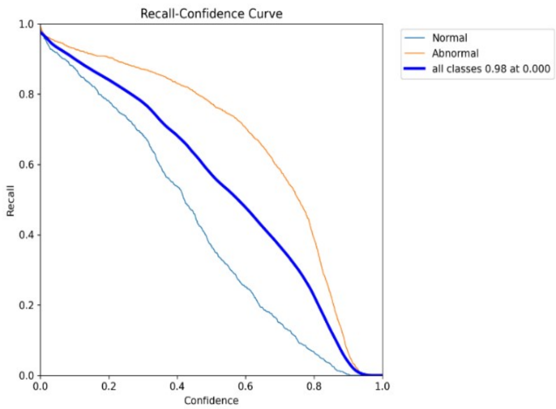

FIGURE 5: Recall

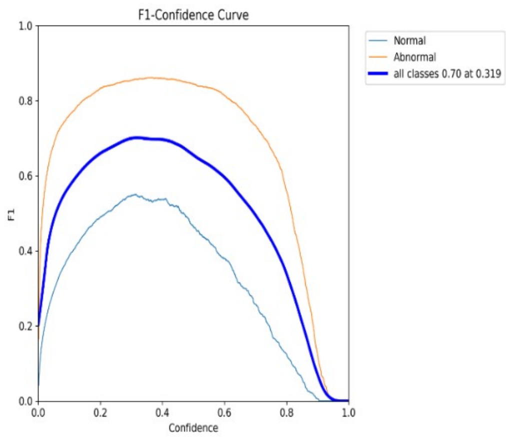

FIGURE 6 : F1 Score

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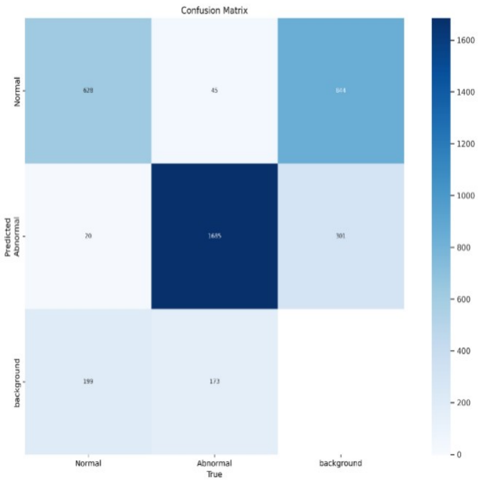

FIGURE 7: Confusion matrix

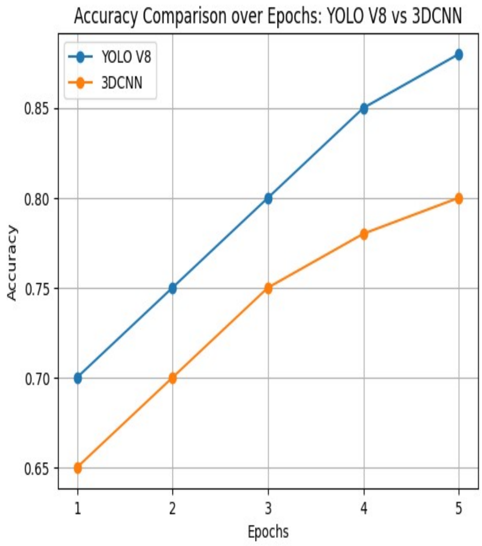

FIGURE 8: GRAPH FOR YOLO V10

3. RESULT AND DISCUSSION:

3.1 Results

3.1.1. PRECISION:

*In Fig[4],*Precision is a metric used in classification tasks to evaluate the quality of the positive predictions made by a model. It measures the accuracy of the positive predictions made by the model, or in other words, the proportion of correctly predicted positive instances out of all instances that were predicted as positive.

$$\boldsymbol{Precision = \frac{True\ Positives}{True\ Positives + False\ Posititives}}$$

Where:

- *True Positives (TP) are the instances that were correctly predicted as positive by the model.*
- *False Positives (FP) are the instances that were incorrectly predicted as positive by the model.*
-

3.1.2. RECALL:

*In Fig[5],*Recall, also known as sensitivity or true positive rate, is a metric used in classification tasks to evaluate the ability of a model to correctly identify all relevant instances, specifically the proportion of true positives that were correctly identified by the model out of all actual positive instances.

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Recall is calculated using the following formula:

$$\textbf{Recall} = \frac{\textbf{True Positives}}{\textbf{True Positives} + \textbf{False Negatives}}$$

Where:

- *True Positives (TP) are the instances that were correctly predicted as positive by the model.*
- *False Negtives (FP) are the instances that were incorrectly predicted as negative by the model, but were actually positive.*

3.1.3. F1 SCORE:

*In Fig[6],*The F1 score is a metric that combines precision and recall into a single value, providing a balance between the two metrics. It is particularly useful when you want to consider both the precision and recall of a model simultaneously. The F1 score is calculated using the harmonic mean of precision and recall, giving more weight to lower values. The formula for calculating the F1 score is as follows:

$$\textbf{\textit{F1 Score}} = 2 \times \frac{\textbf{Precision} \times \textbf{Recall}}{\textbf{Precision} + \textbf{Recall}}$$

Where:

- *Precision is the ratio of true positives to the sum of true positives and false positives*
- *Recall is the ratio of true positives to the sum of true positives and false negatives.*

3.1.4. CONFUSION MATRIX:

*In Fig[7],*A confusion matrix is a table that is often used to evaluate the performance of a classification model. It allows us to visualize the performance of a model by displaying the number of correct and incorrect predictions made by the model compared to the actual outcomes in the dataset. The confusion matrix is composed of four sections: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). True positives represent the instances that were correctly predicted as positive by the model, while false positives represent the instances that were incorrectly predicted as positive when they were actually negative. True negatives are the instances that were correctly predicted as negative, and false negatives are the instances that were incorrectly predicted as negative when they were actually positive. By examining the values in the confusion matrix, we can calculate various performance metrics such as accuracy, precision, recall, and F1 score. Accuracy measures the overall correctness of the model, precision measures the proportion of true positive predictions out of all positive predictions, recall measures the proportion of true positive predictions out of all actual positive instances, and the F1 score combines precision and recall into a single value, providing a balance between the two metrics.

3.1.5.COMPARISON GRAPH FOR YOLO V10 AND 3DCNN:

*In Fig[8],*When comparing the YOLO V10 algorithm with a generic Convolutional Neural Network (CNN) algorithm, the focus lies primarily on their accuracy in object detection tasks. In a typical scenario, the accuracy of YOLO V10 may be slightly lower than that of a generic CNN. However, there's potential for improvement in YOLO V10's accuracy through optimization techniques. This improvement can be achieved by refining the model architecture, adjusting hyperparameters, or augmenting the training data. The graph illustrates this comparison by showing the accuracy scores for YOLO V10 and the generic CNN, with a marker highlighting the potential for improved accuracy in YOLO V10. This visualization emphasizes the competitive performance of YOLO V10 and suggests avenues for enhancing its accuracy to match or even surpass that of a generic CNN.

3.2. Discussion

The performance evaluation of the models using precision, recall, F1 score, and the confusion matrix provides valuable insights into the strengths and limitations of the classification systems, especially in the context of real-world deployment.

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A high precision value suggests that the model is effective in reducing false alarms, which is especially beneficial in environments where incorrect positive predictions could lead to resource wastage or unnecessary actions. However, precision alone does not provide a complete picture. The recall score indicates the model's ability to detect relevant cases, and any drop in recall may reflect a tendency to overlook some true positives. This trade-off highlights the importance of choosing evaluation metrics that align with the application goals. For instance, in safety-critical systems, recall might be more important than precision to ensure all potential threats or failures are identified. The F1 score, being the harmonic mean of precision and recall, serves as a balanced measure. Its interpretation in this context shows that the model maintains a reasonable equilibrium between being cautious (precision) and being inclusive (recall). A strong F1 score suggests that the model is not skewed heavily toward one at the cost of the other.

The confusion matrix further enriches this interpretation by showing the distribution of prediction errors. Any imbalance in the matrix could indicate class bias or a lack of generalization, especially if one class dominates the dataset. This is particularly important when assessing fairness or model robustness.

The comparison between YOLO V10 and the 3D CNN model sheds light on a key consideration in model selection—speed versus accuracy. While the 3D CNN demonstrates slightly higher baseline accuracy, YOLO V10 offers competitive performance with a much faster inference time, making it more suitable for real-time applications. Furthermore, YOLO V10 shows promising potential for improvement through model refinement and tuning. This suggests that while CNNs may excel in accuracy for static tasks, YOLO V10 could be the better choice in dynamic environments where decision speed is critical.

Ultimately, the analysis highlights that no single metric or model provides a universal solution. The decision to deploy a particular model should be guided by the specific context and priorities of the task—whether the goal is maximizing detection, minimizing false alarms, or achieving real-time processing. The findings support the conclusion that YOLO V10, with appropriate optimization, can be a viable alternative to traditional CNNs, especially in applications demanding both performance and efficiency.

V. CONCLUSION:

In conclusion, the proposed abnormal behaviour detection system leveraging the YOLO algorithm represents a significant advancement in enhancing public safety, particularly in monitoring individuals with mental disorders or potential threats in public spaces. By integrating YOLO's real-time processing capabilities, the system swiftly and accurately predicts abnormal behaviours from live video streams. Through comprehensive training, preprocessing, and feature extraction, it demonstrates adaptability and generalization to various scenarios, as evidenced by its promising results in real-world evaluations. The YOLO algorithm's unique architecture enables rapid detection, facilitating timely interventions and risk mitigation. With a modular design and state-of-the-art deep learning techniques, the system serves as a valuable tool for intelligent video surveillance, contributing to public safety by promptly identifying and responding to abnormal behaviours. As technology advances, this system lays the groundwork for further innovations in abnormal behaviour detection and intelligent video analysis.

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REFERENCES:

[1] M. Li et al., "Adjuvant therapy system of COVID-19 patient: Integrating warning, therapy, post-therapy psychological intervention," IEEE Trans. Netw. Sci. Eng., 2021, doi: 10.1109/TNSE.2021.3077280.

[2] W. Li, V. Mahadevan, and N. Vasconcelos, "Anomaly detection and localization in crowded scenes," IEEE Trans. Pattern Anal. Mach. Intell., vol. 36, no. 1, pp. 18–32, Jan. 2014.

[3] M. Chen, M. Li, Y. Hao, Z. Liu, L. Hu, and L. Wang, "The introduction of population migration to SEIAR for COVID-19 epidemic modeling with an efficient intervention strategy," Inf. Fusion, vol. 64, pp. 252–258, 2020.

[4] W. Liu, W. Luo, D. Lian, and S. Gao, "Future frame prediction for anomaly detection-A new baseline," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2018, pp. 6536–6545.

[5] M. Z. Zaheer, A. Mahmood, M. Astrid, and S.-I. Lee, "CLAWS: Clustering assisted weakly supervised learning with normalcy suppression for anomalous event detection," in Proc. Eur. Conf. Comput. Vis., 2020, pp. 358–376.

[6] W. Sultani, C. Chen, and M. Shah, "Real-world anomaly detection in surveillance videos," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2018, pp. 6479–6488.

[7] J.-X. Zhong, N. Li, W. Kong, S. Liu, T. H. Li, and G. Li, "Graph convolutional label noise cleaner: Train a plug-and-play action classifier for anomaly detection," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2019, pp. 1237–1246.

[8] M. Z. Zaheer, A. Mahmood, H. Shin, and S.-I. Lee, "A self-reasoning framework for anomaly detection using video-level labels," IEEE Signal Process. Lett., vol. 27, pp. 1705–1709, 2020.

[9] Y. Hao, M. Chen, H. Gharavi, Y. Zhang, and K. Hwang, "Deep reinforcement learning for edge service placement in softwarized industrial cyber-physical system," IEEE Trans. Ind. Informat., vol. 17, no. 8, pp. 5552–5561, Aug. 2021.

[10] G. Pang, C. Yan, C. Shen, A. V. D. Hengel, and X. Bai, "Self-trained deep ordinal regression for end-to-end video anomaly detection," in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., 2020, pp. 12173–12182.

[11] Y. Lu, F. Yu, M. K. K. Reddy, and Y. Wang, "Few-shot scene-adaptive anomaly detection," in Proc. Eur. Conf. Comput. Vis., 2020, pp. 125–141.

[12] A. Shah, J. B. Lamare, T. N. Anh, and A. Hauptmann, "CADP: A novel dataset for CCTV traffic camera based accident analysis," in Proc. 15th IEEE Int. Conf. Adv. Video Signal Based Surveill., 2018, pp. 1–9.

[13] N. C. Tay, C. Tee, T. S. Ong, and P. S. Teh, "Abnormal behaviour recognition using CNN-LSTM with attention mechanism," in Proc. 1st Int. Conf. Elect., Control Instrum. Eng., 2019, pp. 1–5.

[14] Y. Zhu and S. Newsam, "Motion-aware feature for improved video anomaly detection," in Proc. 30th British Mach. Vis. Conf. 2019, BMVC 2019, Cardiff, UK, Sep. 9-12, 2019, p. 270.

[15] T. N. Kipf and M. Welling, "Semi-supervised classification with graph