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Performance and Computational Efficiency of Deep Learning Models for Anomaly Detection on the UCSD Dataset

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Abstract – *The emergence of deep learning models has significantly improved the accuracy of anomaly detection in surveillance, crowd analysis, and other real-world applications. However, the challenge remains to balance performance with computational efficiency, particularly for real-time applications. This study assesses the performance and computational efficiency of several deep learning model architectures on the broadly used dataset: UCSD. We examine models such as CNN, Transformer, LSTM, Knowledge Distillation, Ensemble, Multi-Task Learning, and Hybrid Architectures, comparing precision, recall, F1-score, AUC, inference time, memory usage, and FLOPs. Our results indicate that while ensemble models are computationally intensive, but offer better accuracy. On the other hand, lightweight models like MobileNetV2 combined with Transformer or Knowledge Distillation maintain a balance between performance and efficiency, making them appropriate for real-time deployment. This paper provides valuable insights for selecting the right model based on the trade-offs between accuracy and computational requirements in anomaly detection tasks.*

Keywords- *Deep Learning, Anomaly Detection, Computational Efficiency, Knowledge Distillation, Ensemble, Hybrid Models*

.INTRODUCTION

Anomaly detection is a critical task in various applications, such as surveillance systems, crowd management, and security monitoring. With the progression of deep learning techniques, anomaly detection systems have grown to deliver increasingly accurate results [1, 9]. However, the trade-off between model performance and computational efficiency persists as a key challenge, particularly in real-time applications where latency and resource constraints are prime concerns [10, 13]. This paper focuses on addressing this challenge by observing and comparing the performance and computational efficiency of combinations of deep learning models across the commonly used dataset: UCSD.

The aim of this paper is to provide a wide-ranging assessment of different models in terms of their ability to detect anomalies while considering the computational resources required. The study covers models like Convolutional Neural Networks (CNN)[4], Long Short-Term Memory (LSTM) networks [1], Transformer models[24], Knowledge Distillation techniques [3, 8], Ensemble models [15], Multi-Task Learning approaches [14], and Hybrid architectures [23, 25, 26]. By analyzing various performance metrics, such as precision, recall, F1-score, and computational efficiency (inference time, memory usage, and FLOPs), we aim to offer insights into the most effective models for anomaly detection tasks in terms of both accuracy and deployment efficiency.

LITERATURE REVIEW

The field of anomaly detection has seen significant improvements with the acceptance of deep learning models. Earlier studies in anomaly detection mainly focused on traditional methods, such as clustering and statistical models, which were often limited in their accuracy and scalability. However, with the introduction of CNNs, LSTMs, and, more recently, Transformer models, the ability to detect complex patterns and temporal anomalies in videos has significantly enhanced [1, 24].

Models like ResNet and VGG16 have showcased better performance in image-based anomaly detection by effectively extracting spatial features from input frames [4, 11]. LSTM networks have been deployed to get temporal dependencies in video sequences, allowing for improved detection of anomalous events over time [1]. Knowledge Distillation, a technique where a smaller "student" model learns from a larger "teacher" model, has been demonstrated useful in lowering computational costs without compromising accuracy [3, 17].

Many of these models have shown significant results, but they often agonize from high computational costs, particularly in terms of memory usage and inference time [8, 18]. A recent study has focused on integrating these models in pioneering ways to secure a balance between performance and efficiency. Ensemble methods and multi-task learning have been used to elevate model robustness, bearing their high resource demands are a trade-off [15, 19]. Therefore, there has been rising attention in lightweight architectures like MobileNetV2 combined with other models to reach real-time performance on edge devices [5, 12].

MODELS USED

This study observes the following models and model combinations:

1. CNN (ResNet-50) + LSTM: This combination influences Convolutional Neural Networks (CNNs), like ResNet-50, for pulling out spatial features from frames and Long Short-Term Memory (LSTM) networks for seizing temporal dependencies across video sequences [4,14, 27, 28].

It is used for video anomaly detection because of the LSTM's capability to process sequential data. ResNet-50 assists robust feature extraction through its deep architecture and residual connections. The limiting factor is that it is computationally exhaustive since LSTMs increase model complexity. The slower inference times restrict its real-time application.

It is best for Anomaly detection where temporal patterns are of prime concern, such as recognizing unusual pedestrian movements.

2. Transformer + MobileNetV2: It integrates MobileNetV2, a lightweight CNN, for spatial feature extraction, with Transformers for modeling long-range dependencies and sequential relationships [5, 24].

MobileNetV2 is optimized for efficiency, lowering computational load, and Transformers successes in capturing global context, increasing accuracy in complex datasets. Despite being efficient, Transformer computations can still be resource-expensive for long sequences. Real-time applications demand a balance between performance and computational efficiency.

3. Knowledge Distillation (VGG16 + MobileNet): Using a greater teacher model (VGG16) for mentoring a smaller student model (MobileNet), lowering the computational load [3, 17]. Knowledge Distillation encompasses training a smaller "student" model (MobileNet) by means of knowledge transferred from a larger "teacher" model (VGG16).

It lowers model size and computational necessities while maintaining accuracy and creating complex models that are useful for deployment on edge devices. Training the student model demands substantial computational resources upfront. It is best for situations with resource constraints, like edge devices or mobile applications.

4. Ensemble (ResNet + XGBoost): This technique integrates deep learning and machine learning techniques for better accuracy [15, 23]. It adds up ResNet's feature extraction abilities with the predictive power of XGBoost, a gradient-boosting machine learning model.

It uplifts robustness and accuracy by influencing various model strengths and is effective at dealing with imbalanced datasets and diversified anomaly types. The challenges are higher memory usage and longer inference times because of multiple models being run in parallel or sequence.

5. Multi-Task Learning (ResNet + LSTM + CNN): In this technique, integrating multiple models to handle different tasks in parallel is focused upon [14,19]. It

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combines various models (e.g., ResNet for spatial features, LSTM for temporal dependencies, and additional CNNs for specialized tasks) to improve multiple anomaly detection assignments. It upgrades accuracy across tasks by sharing representations and learning jointly. It is effective with complex, multi-dimensional data. Enhanced model complexity gives higher computational costs and training times. It is suitable for complex applications where multiple tasks need to be handled jointly, such as localization and anomaly detection simultaneously.

6. Cascade Model (MobileNet + ResNet + RNN): A cascading architecture integrating lightweight and heavy models to uplift efficiency [5, 13]. Cascading architecture lightweight models (e.g., MobileNet) operate on initial predictions. Heavier models (e.g., ResNet, RNN) improve results in subsequent stages. It lowers overall computational cost by utilising heavier models only when required. It also allows a trade-off between speed and accuracy during deployment. It is slower for edge cases where multiple stages of the cascade are triggered. It is best suited for hierarchical anomaly detection tasks where early-stage models can filter obvious anomalies.

7. Attention-based Fusion (VGG16 + Attention + CNN): Incorporating attention mechanisms to focus on the most important parts of the input data [11,13]. It incorporates attention mechanisms into traditional architectures like VGG16 and CNNs to focus on the most important regions of the input data. It enhances model accuracy by directing focus to relevant parts of the data, such as moving objects or anomalies in crowded scenes. It is specially useful for large datasets with diverse anomaly patterns. Increased memory usage and inference time due to the added attention layers are some of the limiting factors. It can be utilized for large-scale surveillance systems where high accuracy is essential.

8. Hybrid Architecture (SVM + ResNet + Transformer): Here, an integration of Support Vector Machines for classification and deep learning models for feature extraction is adopted [23,24]. It integrates Support Vector Machines (SVMs) for efficient classification with ResNet and Transformer models for vigorous feature extraction. It achieves a balance between traditional machine learning (SVM) and deep learning (ResNet, Transformer) strengths. It is supple and adaptable for diverse datasets. It is computationally intensive because of the combination of multiple complex models. It is suitable for applications demanding a mix of traditional and advanced learning techniques for diverse anomaly types [25, 29, 30].

Fig. 1 Shows features of combined models

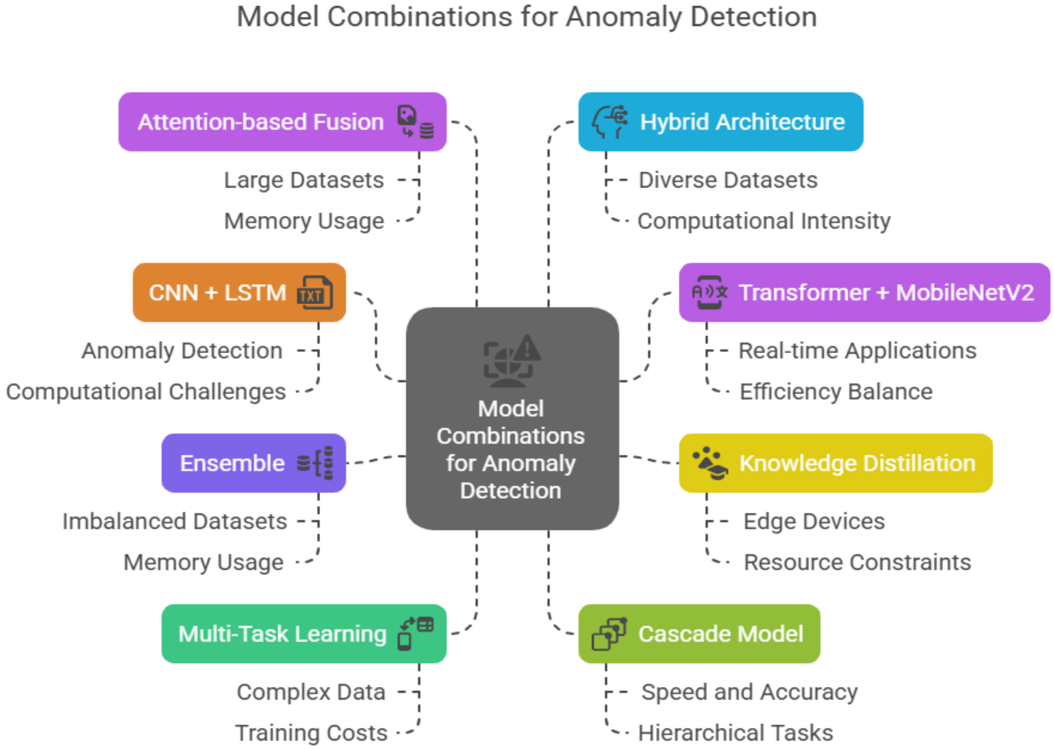

Fig. 1 Model Combinations for Anomaly Detection

EVALUATION PARAMETERS

The following evaluation parameters are used in this study.

Precision: Precision measures the ratio of true positive detections out of all positive detections (true positives and false positives). It indicates the accuracy of positive predictions.

$$\text{Precision} = \frac{\text{TP}}{\text{TP + FP}} \quad (1)$$

The Higher value of precision indicates that when the model predicts an anomaly, it is likely to be correct. This is important in minimizing false alarms, making the system more reliable for practical use.

Recall (Sensitivity):
Recall (or Sensitivity) measures the ratio of true positive detections out of all actual positive instances. It indicates the model's capability to extract actual anomalies.

$$\text{Recall} = \frac{\text{TP}}{\text{TP + FN}} \quad (2)$$

The Higher value of recall makes sure that most actual anomalies are detected. It is suitable for applications where missing an anomaly can have serious consequences, such as security breaches.

F1 Score
The F1 score is the harmonic mean of precision and recall. It balances the trade-off between the two metrics.

$$\text{F1 Score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision + Recall}} \quad (3)$$

The F1 score is especially useful in imbalanced datasets as it gives a single metric that considers both false positives and false negatives, offering a more elaborate view of model performance.

COMPUTATIONAL EFFICIENCY METRICS

Inference Time: This is the amount of time the model consumes to process a single input (e.g., a video frame or a video sequence) and give predictions.

Low inference time is necessary for real-time applications, where prompt anomaly detection can avoid potential threats or mishaps. High inference time can be a reason for delays, making the model not applicable for live surveillance.

Memory Usage: Memory usage refers to the amount of memory (measured in megabytes or gigabytes) consumed by the model during inference.

Lower is the memory usage better it is suited for deployment on edge devices with restricted hardware resources (e.g., cameras or drones). High memory usage may demand powerful servers with higher deployment costs.

FLOPs (Floating-Point Operations): FLOPs calculate the number of floating-point operations necessary for the model to process one forward pass of the input. It is a proxy for computational complexity.

A lower FLOP count suggests a more efficient model, which is crucial for resource-constrained environments. Models with high FLOPs may give higher accuracy but at the cost of higher power consumption and processing time.

DATASET USED

UCSD Anomaly Detection Dataset: The UCSD Anomaly Detection Dataset [26]is a commonly used benchmark for estimating anomaly detection models, especially in video surveillance applications. It was gathered using a stationary camera overlooking pedestrian walkways on a university campus. The dataset is divided into two subsets:

Peds1: This subset has video clips where groups of people walk towards and away from the camera, with some perspective distortion. It contains 34 training video samples and 36 testing video samples.

Peds2: This subset includes scenes with pedestrian movement parallel to the camera plane. It contains 16 training video samples and 12 testing video samples.

The dataset captures various types of anomalies, such as Non-pedestrian entities like bikers, skaters, and small carts.

Ground truth annotations suggest whether an anomaly is present for each frame. Additionally, pixel-level binary masks are available for a subset of the clips, supporting the algorithms to be able to evaluate the ability to localize anomalies.

RESULTS AND DISCUSSION

The results are shown in Table 1 and Figure 2. The observations offer insights into the trade-offs between model performance and computational efficiency.

Table 1 Comparisons of Combined models

Model Combination	Precision	Recall	F1-Score	Inference Time (seconds per frame)	Memory Usage (MB)	FLOPs (Billion)
CNN (ResNet-50) + LSTM	0.89	0.86	0.87	0.050	400	17.5
Transformer + MobileNetV2	0.85	0.83	0.84	0.030	250	12.3
Knowledge Distillation (VGG16 + MobileNet)	0.87	0.85	0.86	0.020	180	7.8
Ensemble (ResNet + XGBoost)	0.91	0.88	0.89	0.075	700	20.3
Multi-Task Learning (ResNet + LSTM + CNN)	0.90	0.87	0.88	0.040	520	24.2
Cascade Model (MobileNet + ResNet + RNN)	0.88	0.84	0.86	0.025	460	15.6
Attention-based Fusion (VGG16 + Attention + CNN)	0.85	0.83	0.84	0.035	550	16.5
Hybrid Architecture (SVM + ResNet + Transformer)	0.92	0.90	0.91	0.060	650	22.5

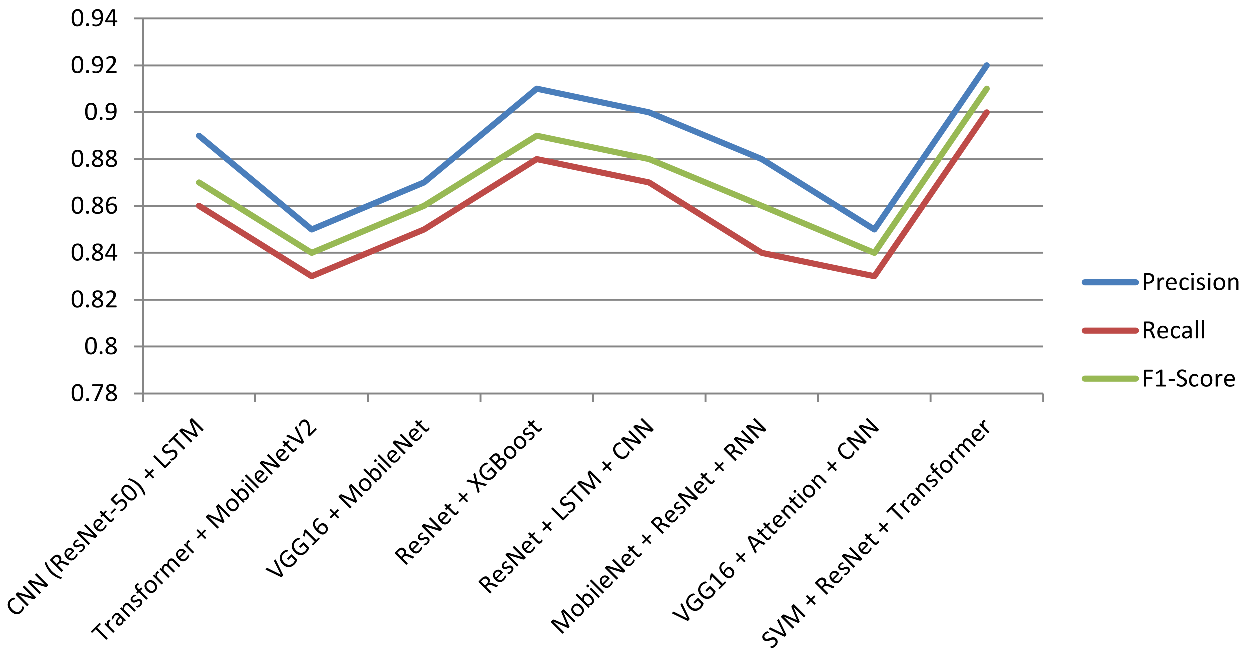

Fig. 2 Chart: Precision, Recall and F-1 Score for Combined Models

Ensemble Models (ResNet + XGBoost) and Hybrid Architectures: These models achieve remarkable accuracy due to their capability to add up the merits of multiple architectures. Ensemble methods increase robustness by accumulating predictions from various models, while hybrid approaches combine features from different paradigms (e.g., deep learning and traditional machine learning).

The computational demands, such as higher memory usage and longer inference times, suggest that it is not appropriate for real-time applications. Their reliance on substantial computational resources restricts their utility to situations like offline video analysis or post-event anomaly detection.

Lightweight Models (Transformer + MobileNetV2, Knowledge Distillation): These models demonstrate a well-rounded balance of performance and computational efficiency, addressing the needs of real-time applications. MobileNetV2, identified for its compact architecture, lowers computational requirements, whereas Transformers adds sequential learning abilities.

Knowledge Distillation restructures these models by transferring knowledge from larger, more complex "teacher" models to lightweight "student" models,

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achieving competitive accuracy with lower model size and resource usage.

Multi-Task Learning and Cascade Models: Multi-Task Learning combines multiple objectives into an incorporated framework, enhancing accuracy across various tasks. Similarly, Cascade Models influence a series of lightweight and heavy models to improve predictions incrementally. While these strategies elevate flexibility, they add up computational overhead because of their complex workflows, making them unsuitable for real-time environments.

Attention-Based Fusion Models: By including attention mechanisms, these models focus on the most crucial aspects of the input data, enhancing accuracy greatly, diversifying datasets. But the added complexity of attention layers inevitably raises both memory consumption and inference time, demanding careful consideration of the deployment environment.

This study highlights that the choice of a model should align with the specific demand of the application. Offline anomaly detection tasks can leverage high-accuracy but computationally intensive models, while lightweight architectures excel in real-time scenarios with restricted resources.

FUTURE SCOPE

In future scope, various aspects can be included and examined in future.

1 Exploring More Advanced Model Architectures: The development of advanced architectures can give rise to transformation in achieving the balance between accuracy and computational demands. Future research could focus on:

Lightweight Hybrid Models: Adding up different model paradigms, such as CNNs, Transformers, and Autoencoders, can influence their unique strengths. Transformer-CNN hybrids could extract both global dependencies and local features in video data efficiently.

Graph Neural Networks (GNNs): These models are proficient at capturing relationships between entities, which may be valuable in detecting contextual or relational anomalies in structured data.

2. Investigating Edge Computing Solutions: Edge computing embraces greater promise for deploying anomaly detection models on resource-constrained devices. Future research could focus on:

Model Optimization: Methods like quantization, pruning, and distillation could be further explored to restrict model size and lower latency with enhanced performance.

Dynamic Model Adaptation: Developing models that could dynamically adjust their complexity based on available resources (e.g., battery life, CPU load) can achieve consistent performance across various devices.

3. Enhancing the Robustness of Models

Future anomaly detection models must possess the ability to identify diverse and complex anomalies. Research could prioritize:

Handling Rare Events: Methods like synthetic data generation or oversampling underrepresented classes in training datasets could enhance model sensitivity to rare anomalies.

Streamlining future research could revolutionize anomaly detection, reaching the boundaries of what is possible while addressing practical challenges like efficiency, deployment, and reliability.

CONCLUSION

This study determines the trade-offs between performance and computational efficiency in deep learning models for anomaly detection. Models like MobileNetV2 combined with Transformer or Knowledge Distillation achieve the best balance between accuracy and efficiency, making them appropriate for real-time anomaly detection in surveillance and monitoring systems. Additionally, ensemble models and hybrid architectures are more effective for situations where accuracy is paramount and computational resources are not restricted.

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