# Ingure Thesis summrise (reza)

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Abstract—The abstract goes here.

## I. Introduction

### A. Advances in AI and Deepfakes

The development of Artificial Intelligence (AI) and deep learning technologies has significantly advanced computer vision and image generation capabilities. A key outcome of these advancements is the enhancement of deepfakes, which are AI-generated images and videos that can swap faces with a high degree of realism. While this technology has brought value to creative fields such as filmmaking and special effects, it has also raised ethical concerns. The ability to manipulate videos to make people appear to say or do things they never did presents serious risks to privacy, security, and trust in digital media. Therefore, detecting and mitigating deepfakes has become essential to protect potential victims of such manipulations.

### B. Early Approaches in Deepfake Detection

Initially, Convolutional Neural Networks (CNNs) were used to identify deepfakes, as they had proven successful in various computer vision tasks. Early CNN-based models showed effectiveness in identifying first-generation deepfakes. However, as datasets became larger and more complex, these models required further advancements to improve both their accuracy and capacity to handle diverse and sophisticated deepfakes.

### C. Shifting to Transformers in Vision Research

In 2020, researchers began exploring the potential of transformer-based models for computer vision tasks, inspired by their success in Natural Language Processing (NLP). Transformers, particularly those with the self-attention mechanism, became a preferred model due to their ability to capture long-range dependencies within data. The Vision Transformer (ViT) was introduced as an alternative architecture that, unlike CNNs, processes images as a series of patches rather than pixel-based grids. This novel approach leveraged large datasets and pre-training, allowing ViTs to perform on par or even better than state-of-the-art CNN models in some cases.

### D. Challenges with Vision Transformers in Deepfake Detection

Despite their success, Vision Transformer-based models still face certain challenges in deepfake detection, particularly in terms of resource requirements. ViTs often demand high computational power and memory, which becomes problematic in real-time or resource-constrained environments, such as on edge devices. To address these bottlenecks, researchers continue to explore methods that balance accuracy with efficiency.

### E. Model Compression Techniques

Recent efforts have focused on reducing the computational cost of models through techniques like quantization, knowledge distillation, and pruning. These approaches compress model sizes by lowering the precision of weights without significantly altering the architecture. Among these, post-training quantization (PTQ) has been widely adopted due to its simplicity and its ability to minimize memory use while speeding up model inference. However, these methods often lead to some loss in accuracy, especially at lower precision levels.

### F. Quantization-Aware Training (QAT)

To mitigate the loss of accuracy, Quantization-Aware Training (QAT) has been introduced. This approach allows models to adapt to reduced precision during the training phase itself, leading to better performance during inference, albeit with higher resource demands during training.

### G. BitLinear Layer and Efficient Deepfake Detection

More recently, BitNet introduced the BitLinear layer, which replaces traditional linear layers with ternary-weighted layers (-1, 0, +1). This innovation reduces both memory and energy consumption, making transformers more scalable and efficient. Motivated by the need for more resource-efficient models, this thesis investigates how BitLinear layers can enhance Vision Transformers for deepfake detection, especially in resource-constrained settings.

### H. Key Research Questions

This work seeks to address the following questions:

1) How can Vision Transformers be adapted to effectively detect deepfakes in environments with limited resources?
2) What impact do BitLinear layers have on the performance, size, and speed of Vision Transformers?
3) How do quantization-aware models compare to post-training quantized models in deepfake detection tasks?

### I. Contributions of This Thesis

To answer these questions, this thesis aims to:

1) Implement the BitLinear layer in custom networks, building on the BitNet framework.
2) Pre-train two Vision Transformer models, one using full-precision linear layers and another utilizing BitLinear layers, on ImageNet-1k.
3) Fine-tune these models on multiple deepfake datasets (e.g., FF++, Celeb-DF), and compare their detection performance.
4) Quantize a baseline model to evaluate the effectiveness of QAT and PTQ techniques in the context of deepfake detection.

## II. Literature review

### A. Dataset

Modern deepfake generation techniques have evolved from early methods like 3D morphable models and autoencoders to more advanced techniques, including GANs (e.g., StyleGAN, FSGAN) and diffusion models, which have significantly improved the realism of synthetic faces. To support the advancement of deepfake detection, various datasets have been developed over time, categorized into three generations. The first generation includes small datasets like UADFV, DF-TIMIT, and FaceForensics++, which provided early benchmarks. The second generation, featuring Google DFD, DFDC Preview, and Celeb-DF, introduced higher-quality deepfakes, with Celeb-DF being one of the most widely used. The third generation, including the DeepFake Detection Challenge (DFDC) and Deeper Forensics, expanded the dataset size and diversity, addressing limitations such as the number of swapped identities.

### B. CNNs

Deepfake detection is fundamentally an image classification task, requiring models to distinguish between real and manipulated faces. Early research primarily used Convolutional Neural Networks (CNNs) due to their success in image classification, with MesoNet being one of the first deep learning methods developed for this purpose in 2018. MesoNet's compact architecture targets mid-level features for efficient detection, while MesoInception extended its capabilities by capturing multiscale features.

Li and Lyu advanced detection by using larger CNN models (e.g., ResNet) to identify warping artifacts in deepfake videos. They trained their models on UADFV and DF-TIMIT datasets, showing that ResNet50 performed best. Another notable approach involved combining VGGFace with ResNet50, achieving high accuracy on datasets like FF++ and Celeb-DF.

Recent work has also compared models using full-face inputs versus specific facial regions. Results consistently show that models using entire face inputs outperform region-based models. Finally, the DeepFake Detection Challenge revealed that ensemble learning and frame-by-frame classification generally produce better results. Top-performing solutions utilized models like EfficientNet and XceptionNet, with techniques such as augmentations and MixUp for improved accuracy.

### C. Transformer

The Transformer architecture, introduced in 2017, was primarily designed for Natural Language Processing (NLP) tasks. It leveraged a self-attention mechanism to capture long-range dependencies in data. However, initial applications in computer vision were limited due to the computational demands of applying self-attention to high-dimensional data like images.

In 2020, Dosovitskiy and colleagues introduced Vision Transformers (ViT), building on the successes of transformers in NLP. ViT processes images by splitting them into patches, treating each patch as a token. This patch-based approach enabled the efficient application of self-attention, allowing the model to capture complex relationships in the image while maintaining computational feasibility. ViTs rely heavily on pre-training with large datasets to address the lack of inductive biases (like locality) found in CNNs, achieving performance comparable to CNNs on various image benchmarks.

Vision Transformers are utilized in deepfake detection in two primary ways: either following CNNs as feature extractors or fully replacing CNNs. The CViT model combines CNN and ViT elements, utilizing CNNs for local feature learning and ViTs for global features, enhancing the detection of complex relationships. CrossViT further improves performance by using a multiscale approach, processing both small and large image patches.

DeiT (Data-Efficient Image Transformer) incorporates a student-teacher strategy with distillation tokens to speed up training and improve performance with limited data. Additionally, self-supervised learning (SSL) has been explored to further enhance ViT's capabilities in deepfake detection, particularly in cases where labeled data is scarce.

### D. Quantization

As Transformer architectures scale in size and complexity, their computational and memory requirements also

increase, posing challenges for real-world applications, particularly in resource-constrained environments. To address these issues, various model compression techniques have been explored, such as knowledge distillation (e.g., DeiT), weight pruning, and quantization.

Quantization, a process that reduces model precision by mapping high-precision weights to lower bit-widths, is particularly effective for compressing Transformer models. PTQ is widely adopted as it allows for quantization without retraining, although it often results in accuracy loss, especially with lower bit-widths (e.g., 3 bits or fewer).

QAT mitigates the accuracy loss seen in PTQ by training the model with quantization in mind from the start. Although it maintains higher accuracy at inference, it demands greater computational resources and longer training times. QAT also requires retraining the model from scratch, making it more resource-intensive than PTQ.

In efforts to improve power efficiency and reduce memory consumption, binary and ternary quantization schemes are employed. These methods simplify computations by replacing expensive floating-point operations with efficient bitwise ones. For example, Binary and Ternary Neural Networks (BNNs and TNNs) are utilized in vision tasks to further optimize model performance.

In the domain of language models, BitNet demonstrated the scalability of 1-bit quantization. The BitLinear layer combines 8-bit activation quantization with binary weights trained using QAT, replacing all linear layers in the model. More recently, BitNet b1.58 introduced ternary weights, maintaining performance while improving computational efficiency. These advancements hold promise for applying BitLinear layers to Vision Transformer (ViT) models, potentially making them more efficient while retaining high classification accuracy.

## References

[1] H. Kopka and P. W. Daly, A Guide to LaTeX, 3rd ed. Harlow, England: Addison-Wesley, 1999.