

## Motivation

The increasing complexity and energy demands of modern AI models, such as Vision Transformers (ViTs), pose challenges for their deployment in resource-constrained and real-time environments. This research investigates field-programmable gate arrays (FPGAs) as an efficient hardware platform for AI acceleration. By minimizing and adapting these models for FPGAs, we aim to:

- Reduce Energy Footprint
- Optimize Model Size
- Enhance Efficiency

## Goals

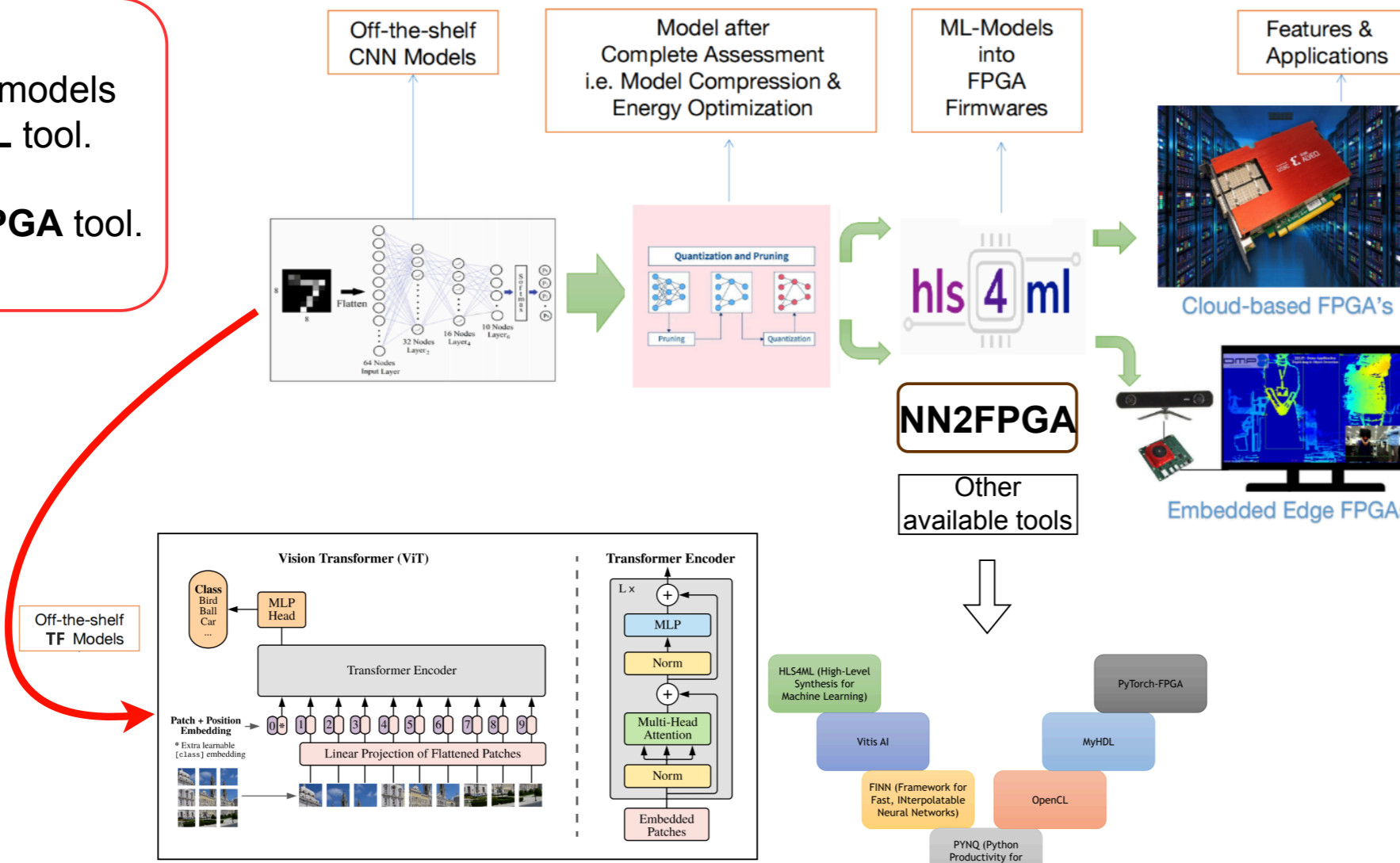
- To minimize and synthesize modern AI models, such as Vision Transformers (ViTs), for small-scale scenarios.
- To analyze the trade-offs, energy consumption, and performance of these models when deployed on FPGAs.
- To evaluate the **feasibility** of using FPGAs as an alternative hardware platform for deploying transformer models in real-time classification tasks.

## Methodology

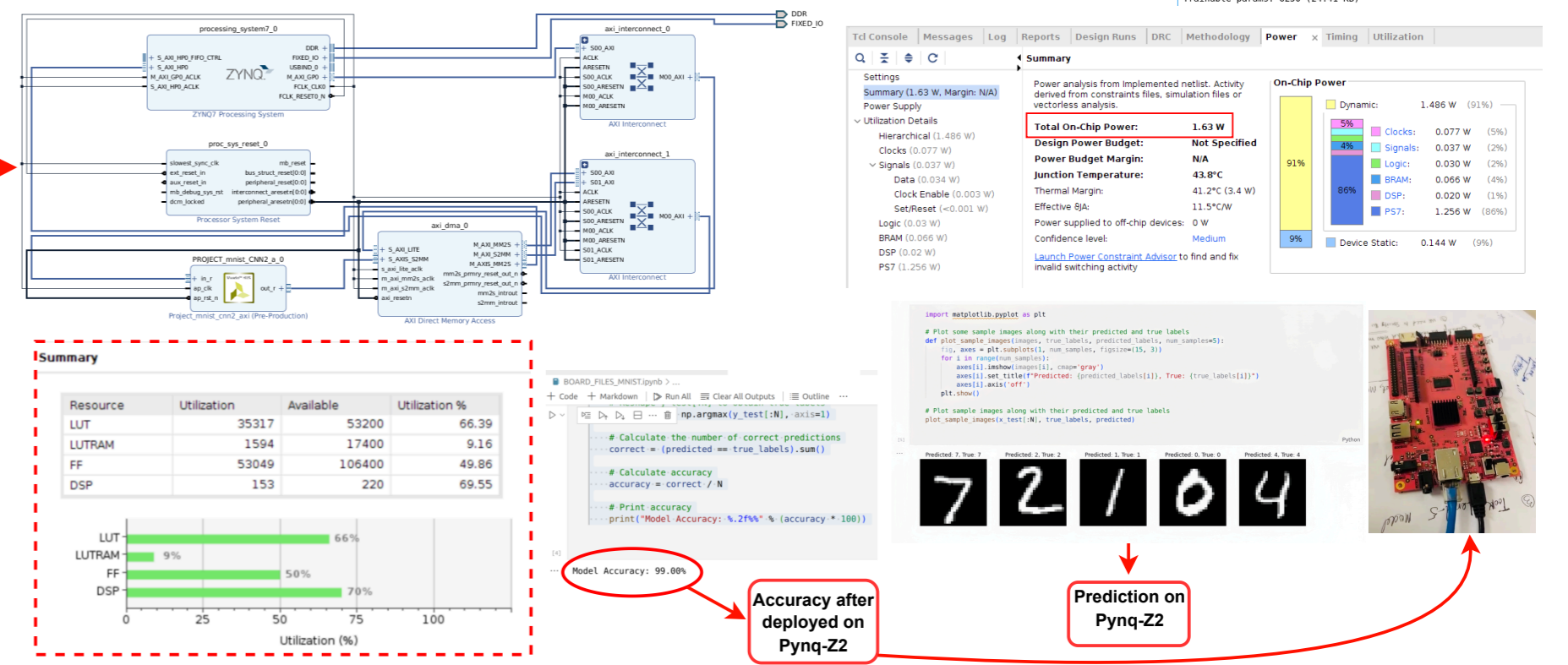
First attempt: CNN models using the HLS4ML tool.  
Next: ViTs on NN2FPGA tool.

Key Challenges:

- Replacing LN with BN.
- Computation strategies for Softmax and GELU.
- ...

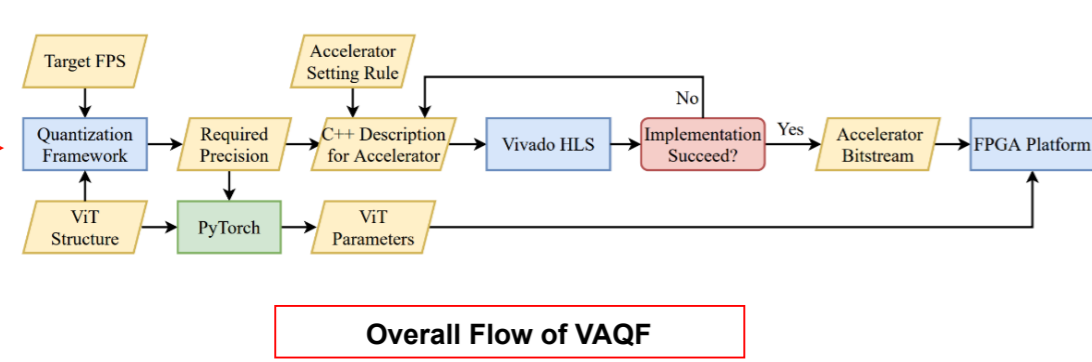


Initial results demonstrate successful deployment of a high-accuracy CNN on a Pynq-Z2 FPGA for MNIST digit classification using HLS4ML. Optimization techniques achieve 99% accuracy with reduced resource usage (LUT 66.39%, LUTRAM 9.16%, FF 49.86%, DSP 69.55%) and power consumption, highlighting the potential for efficient deep learning on edge devices.

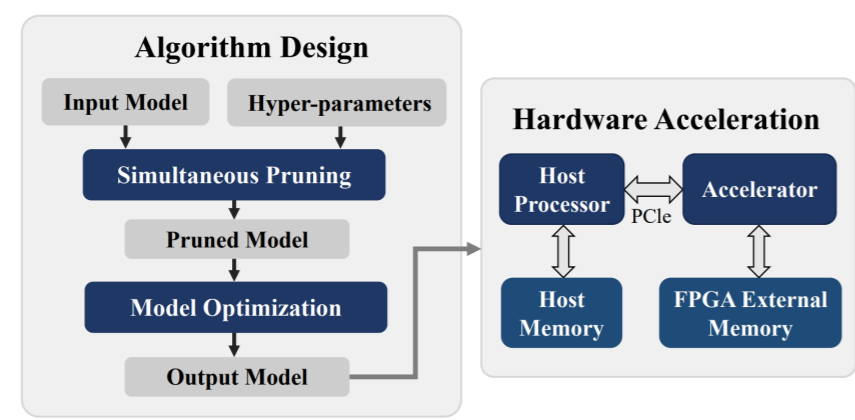


## Related Work

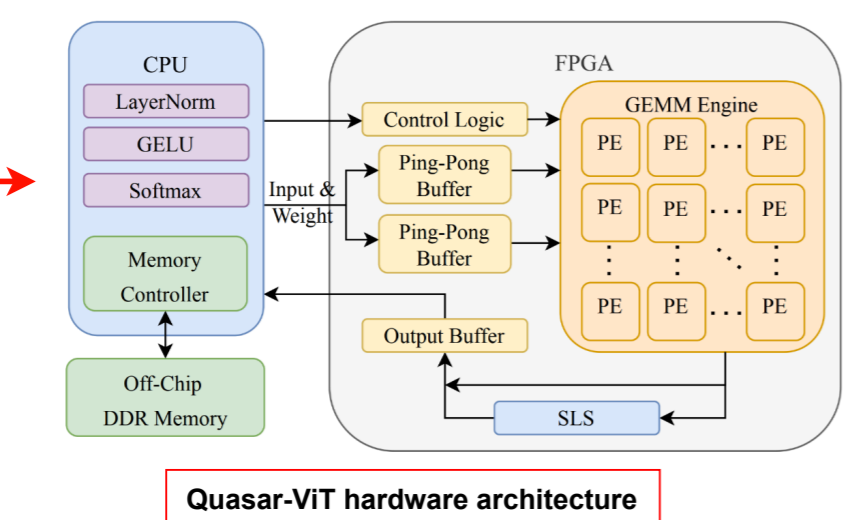
VAQF is a framework that automatically builds efficient, real-time Vision Transformer accelerators on FPGAs by optimizing quantization and hardware parameters.



A novel algorithm-hardware codesign combines both static weight and dynamic token pruning for efficient Vision Transformer execution on a new accelerator.

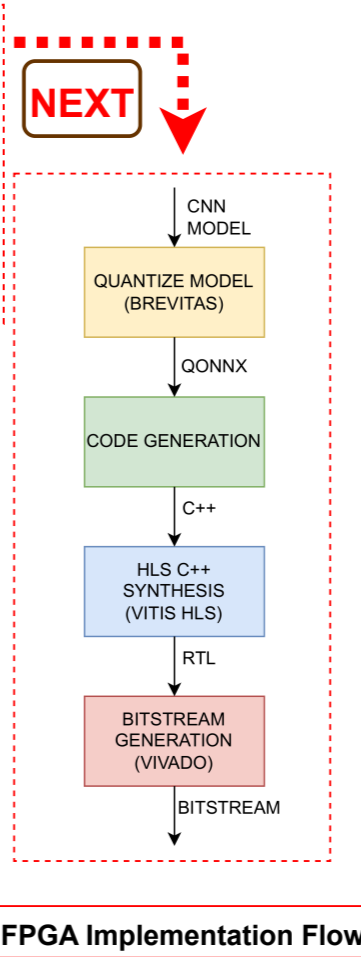
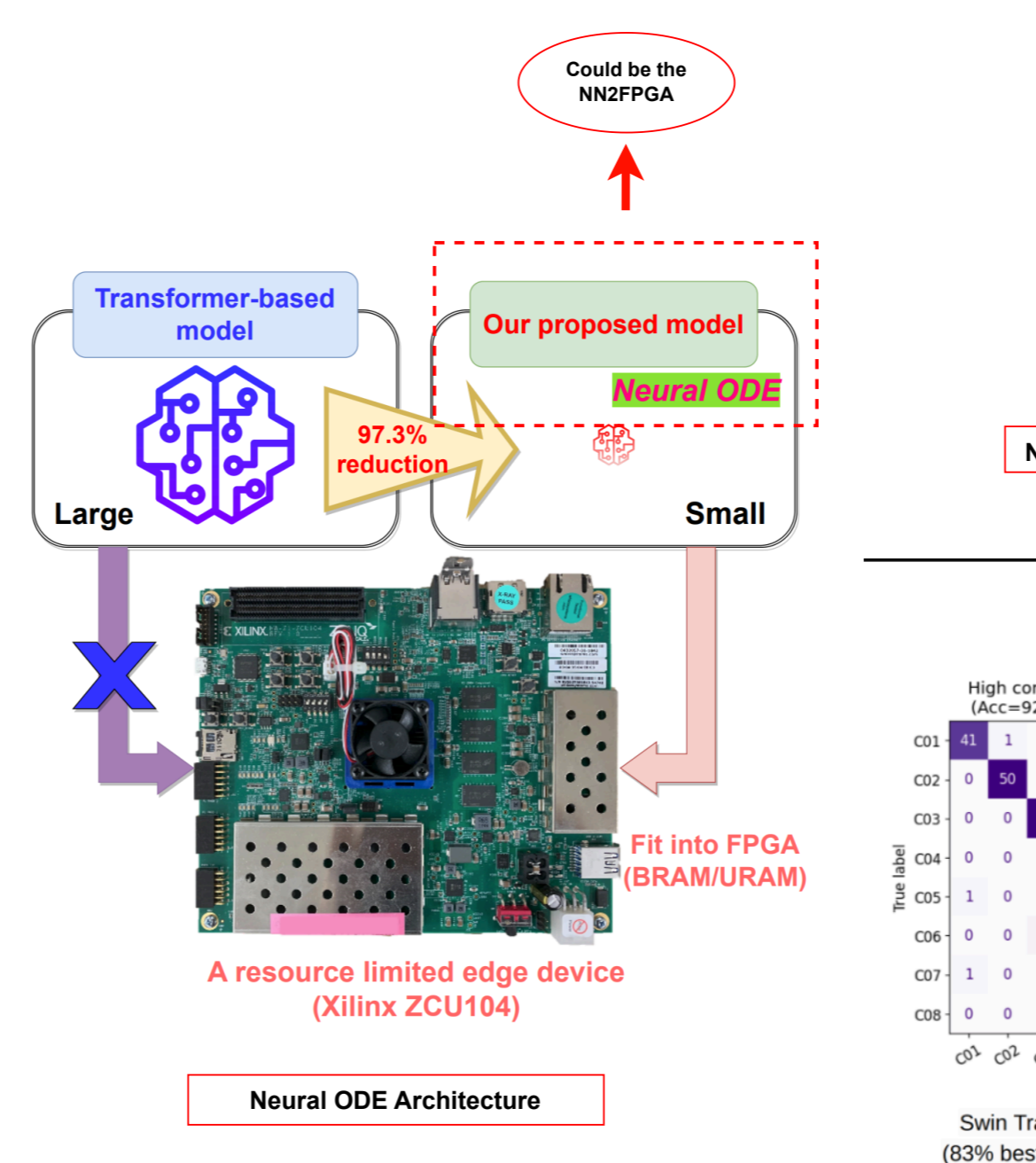
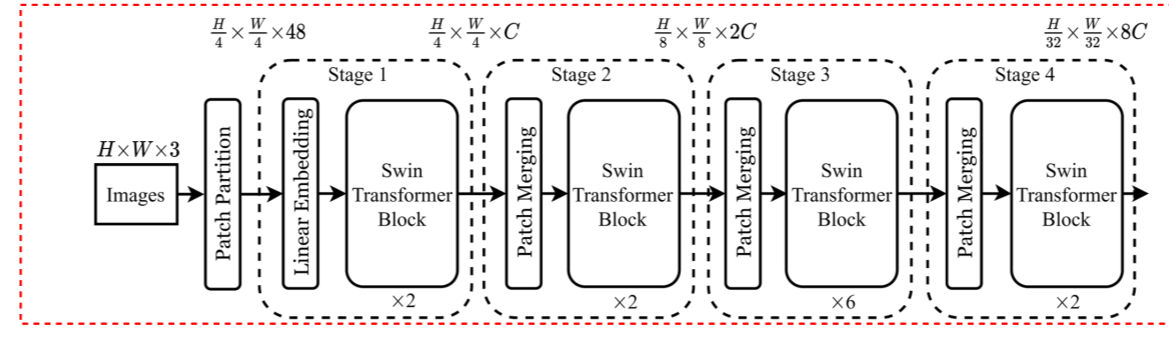


Quasar-ViT is a framework that designs efficient and accurate Vision Transformers for edge devices through hardware-aware quantization and architecture search, achieving high inference speed on FPGAs.



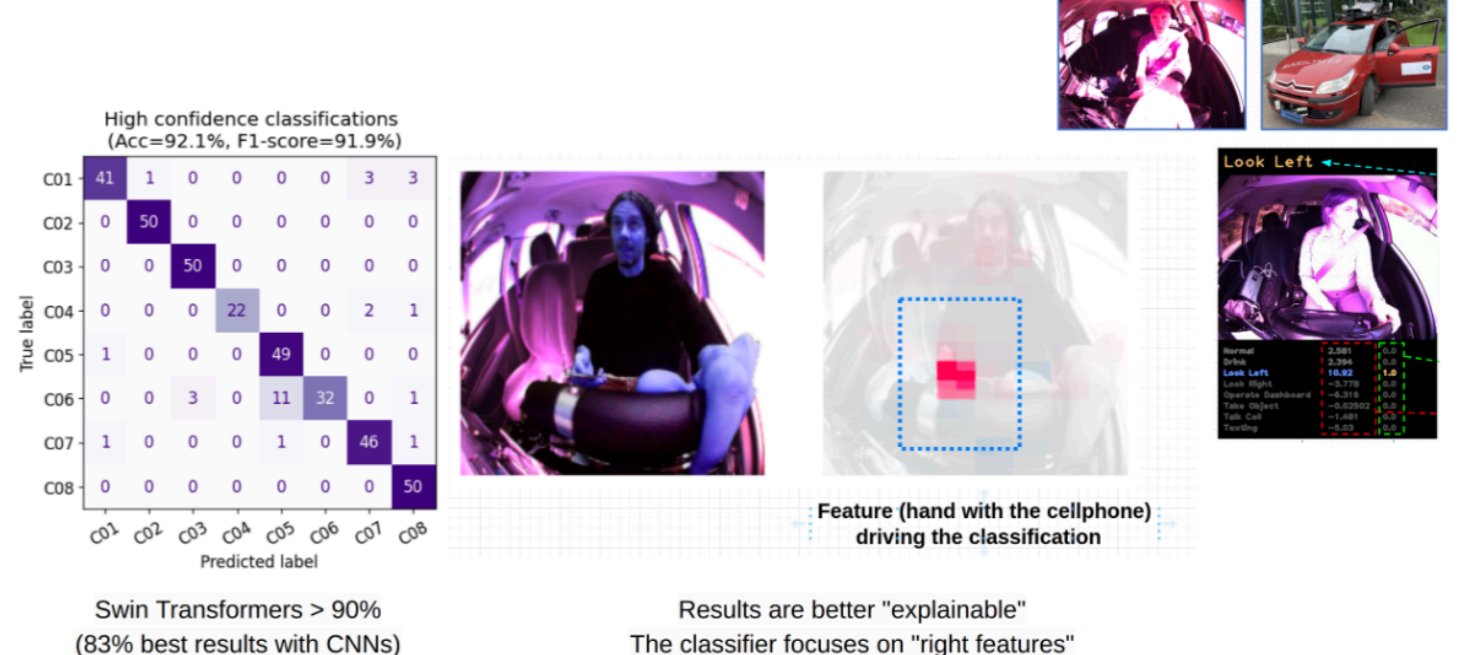
Layer Normalization (LN) was replaced with Batch Normalization (BN) to enable fusion with linear layers, improving inference efficiency on the FPGA with minor accuracy loss.

## Current Work



- Dataflow architecture
- Fixed-point quantization
- Compatible with AMD-Xilinx boards
- High throughput/low power tasks
- Optimized design for skip connections

Possible application: comparison with GPU-based alternative



## Conclusions & Future Work

- Our initial experiments using the HLS4ML framework on the Pynq-Z2 board achieved promising results, demonstrating the feasibility of deploying complex neural networks on FPGAs.
- After successfully deploying ResNet models using NN2FPGA on Kria KV-260 and Ultra96-v2 boards, we are now exploring its compatibility with ViT models and identifying any unsupported parameters.
- **Test Transformer Models:** Implement Swin TF model using NN2FPGA, focusing on maintaining accuracy.
- **Select FPGA Platform:** Choose the best FPGA for deployment, comparing cloud and edge options.
- **Compare GPU and FPGA:** Evaluate performance and energy use for models deployed on GPU and FPGA.

## References

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