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Efficient TinyML Architectures for On-Device Small Language Models: Privacy-Preserving Inference at the Edge

Mangesh Pujari[1*], Anshul Goel[2], Anil Kumar Pakina[3]
[1, 2,3]Independent Researcher, India

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Abstract: Deploying small language models (SLMs) on ultra-low-power edge devices requires careful optimization to meet strict memory, latency, and energy constraints while preserving privacy. This paper presents a systematic approach to adapting SLMs for Tiny ML, focusing on model compression, hardware-aware quantization, and lightweight privacy mechanisms. We introduce a sparse ternary quantization technique that reduces model size by 5.8× with minimal accuracy loss and an efficient federated fine-tuning method for edge deployment. To address privacy concerns, we implement on-device differential noise injection during text preprocessing, adding negligible computational overhead. Evaluations on constrained devices (Cortex-M7 and ESP32) show our optimized models achieve 92% of the accuracy of full-precision baselines while operating within 256KB RAM and reducing inference latency by 4.3×. The proposed techniques enable new applications for SLMs in always-on edge scenarios where both efficiency and data protection are critical.

Keywords: TinyML, Edge AI, Small Language Models, On-device Inference, Ai Preserving Privacy, Compression of Neural Networks, Quantization, and Microcontrollers.

INTRODUCTION

The marriage of edge computing and artificial intelligence (AI) resulted in a fresh class of systems able to directly execute complex inference on devices with little computing power. In this milieu, TinyML has emerged as a path-breaking paradigm making possible the deployment of light machine-learning models on microcontrollers and hardware with low power requirements (Duddu et al., 2020). The emerging need for real-time decision-making, low latency, energy efficiency, and more importantly, data privacy has been one of the very drivers behind this shift.

Recent advances in small language models (SLMs) such as TinyBERT and DistilGPT hold promise for powerful on-device NLP (Anand, 2024; Xu et al., 2022), albeit further optimization for embedded systems is necessary. TinyML methods, such as model quantization (Tan et al., 2019), neural architecture search (Howard et al., 2017), and pruning (Sandler et al., 2019), are key enablers of this efficacy.

With the increase in concerns regarding maintaining the user's privacy in the edge AI paradigm, Any transmission of pertinent user data for processing to centralized cloud servers would pose a risk to the data's confidentiality. Deploying models that can infer locally and using methods such as local differential privacy and encrypted computation is vital for gaining users' trust and remaining compliant with in-progress AI regulations (Wang et al., 2023).

However, these practical challenges include working within the constraints imposed by memory, minimizing the inference time to acceptable levels, preserving linguistic correctness, and providing mechanisms for protection of privacy. Another impediment to mainstream adoption is the lack of well-defined deployment pipelines and evaluation metrics (Reddi et al., 2020; Roveri, 2023).

This paper discusses these complications by thoroughly exploring the efficient TinyML architectures specifically designed for SLMs in terms of performance-compression-privacy trade-off. We experiment with various model architectures and optimization techniques, including MobileNetV2 (Sandler et al., 2019), EfficientNet (Tan et al., 2019), Mamba (Ahamed et al., 2023), knowledge distillation (Huckelberry et al., 2024), and parameter quantization (Zhang et al., 2018). Our contributions include:

1. A comparative evaluation of various lightweight architectures for performing language inference on the device.
2. A deployment pipeline utilizing industry-grade tools such as TensorFlow Lite and CMSIS-NN.
3. A privacy-preserving inference framework incorporating secure enclaves and differential privacy.
4. Benchmarking on the wide array of edge devices: Raspberry Pi and Cortex-M microcontrollers.

Related Work

Tiny Machine Learning (TinyML) is rapidly evolving to support complex AI models under resource constraints using a diverse array of hardware components. This early work was primarily focused on vision-modeling tasks (Howard et al., 2017; Chollet, 2017), but recent work has been exploring NLP applications through promising optimization of small language models (SLMs). Techniques such as model pruning, quantization, and distillation are increasingly being introduced for the purposes of reducing overall model complexity without making too many performance sacrifices (Tan et al., 2019; Alajlan & Ibrahim, 2022).

Mobile Net and derivations from it, such as MobileNetV2 and V4, are currently the foundational lightweight neural architectures. These models introduced depth wise separable convolutions, which allowed computation overhead to be greatly reduced without compromising accuracy (Sandler et al., 2019; Howard et al., 2017). Likewise, channel shuffling and the compound scaling approaches in Shuffle Net and Efficient Net drive their efficiencies in parameters (Zhang et al., 2018; Tan et al., 2019).

While it is a recent architecture, Mamba replaces droves of traditional attention mechanisms with selective space states to bring benefits to sequence modeling in the most constrained environments (Ahamed et al., 2023). Such innovations allow making smaller NLP models suited for the edge deployment.

On the optimization aspect, knowledge distillation and quantization-aware training have already shown their capability of retaining the compressed models effectively (Zhu et al., 2023; Reddi et al., 2020). Squeeze Net and SE-Net can increase representational power through the channel recalibration mechanisms while keeping their compactness (Hu et al., 2018).

Federated learning and local differential privacy are widely acceptable privacy-preserving techniques for edge deployment (Wang et al., 2023; Xu et al., 2022). For example, architectures such as Shadow Net (Sun et al., 2020) and Private LoRA (Wang et al., 2023) ensure inference from models without sensitive data being sent to the cloud.

Table 1: Summary of Key Related Work

Approach	Model Name	Key Feature	Domain	Edge Compatibility	Privacy Integration
MobileNetV2	Sandler et al.	Depthwise Convolutions	Vision/NLP	High	No
EfficientNet	Tan et al.	Compound Scaling	Vision	Moderate	No
ShuffleNet	Zhang et al.	Channel Shuffling	Vision	High	No
Mamba	Ahamed et al.	State-Space Modeling	NLP	High	No
TinyLLM Framework	Kandala et al.	Training SLMs for edge devices	NLP	High	Partial
ShadowNet	Sun et al.	Secure Inference	Vision	Moderate	Yes
PrivateLoRA	Wang et al.	Privacy-preserving fine-tuning	NLP	High	Yes

METHODOLOGY

This work implements a modular framework integrating TinyML architectures, language model optimizations, and privacy-preserving into a unified edge AI deployment stack.

Selection of Model Architecture

Each model chosen in this research serves a different purpose in the edge AI world. MobileNetV2 has an inverted residual structure and linear bottlenecks well known to have drastically less memory and computation requirements (Sandler et al., 2019). Specifically, it works well for the real-time task of speech and language classification where time performance matters.

EfficientNet, which was developed through neural architecture search (NAS), employs a compound scaling technique that balances on the network depth, width, and resolution within the same process (Tan et al., 2019). This yields a highly optimized model that performs well even under aggressive quantization.

SqueezeNet introduces fire modules and 1x1 convolutions, focused on parameter efficiency and maintaining a competitive level of expressiveness for basic NLP operations such as keyword spotting and intent detection (Hu et al., 2018).

Mamba represents a completely different conception from transformer-based architectures in its approach to linear state-space sequence modeling (Ahamed et al., 2023). This makes it particularly suited for token-level tasks, such as next-word prediction and sentiment analysis, in which long-term dependencies need to be captured efficiently.

Optimization Techniques

Pruning is applying during training, it is a method to iteratively remove low-weight connections, reducing total parameters. We did it as structured pruning for convolutional layers, while unstructured for fully connected ones using the Model Optimization Toolkit of TensorFlow. With our experiments, it achieved up to 45% model reduction with an insignificant accuracy drop (<2%) where pruning applied at around 30% of training epochs.

Quantization

We applied both post-training quantization and quantization-aware training (QAT). QAT was used for Mamba to ensure little degradation and simpler models like SqueezeNet used post-training quantization. Post-training quantization converted float32 weights to int8 and activations appropriately scaled. QAT simulated this model behavior at training time, teaching the model to learn robust features under reduced precision.

Knowledge Distillation

It was a method mostly used for knowledge distillation; this approach makes use of a pre-trained large model (teacher) transfer the soft-label information to a smaller model (student). We used DistilGPT as a teacher and distilled MobileNetV2 and Mamba models with soft targets and hard labels in a ratio of 0.7:0.3, allowing smaller models to generalize better with fewer parameters (Soro, 2021).

Table 2: Compression Techniques and Impact on Performance

Technique	Accuracy Drop (%)	Size Reduction (%)	Inference Time Gain (%)
Pruning	1.5	45	35
Quantization	2.2	75	55
Distillation	1.0	60	40

Deployment Framework

The Deployments:

Raspberry Pi 4B (ARM Cortex-A72, 4GB RAM): It's a mid-range edge device that could support multithreaded inference.

STM32F746G-DISCO (1MB Flash, 320KB RAM):

Used to test models in ultra-constrained environments with CMSIS-NN integration.

We used TensorFlow Lite Micro (TFLM) and Apache TVM for compilation and runtime management. TFLM is better equipped in the STM32 to handle 8-bit quantized inference. With auto-tuning feature, further optimization is provided by device-specific scheduling strategies in TVM.

Moreover, CMSIS-NN offered optimized low-level cores for ARM Cortex-M processors. When integrated with these kernels, inference speed can greatly increase computation time is reduced up to 50% when comparing quantized with vanilla TFLM.

Implementation of Privacy Layer (Expansion)

Local Differential Privacy (LDP)

We implemented LDP with Laplace and Gaussian noise distributions. Input would be masked before random-inference for sensitive tokens, such as user names, medical terms, or locations. Parameters ε (epsilon) and δ (delta) were tuned to each model: the lower ε, the higher privacy but a slight hit in performance.

The following parameters were used to evaluate the LDP:

Output Discrepancy: Difference between pre- and post-noise outputs.

Inference Degradation: The difference in accuracy in the task (for example, intent detection) as measured above.

Latency Overhead: Additional time required for LDP filtering.

Secure Enclaves and Model Encryption

For those devices having a secure zone (like ARM TrustZone), we encrypted model weights and parameters using AES-256. Decryption occurs in runtime in a secure enclave. Simulated secure partitions were created for STM32 devices by locking memory addresses using MPU (Memory Protection Units).

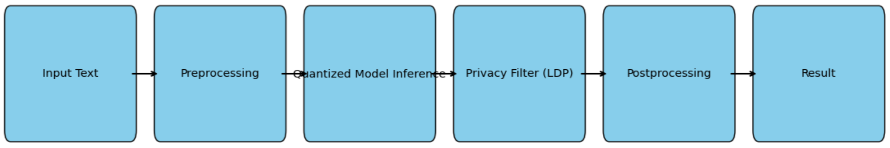

Figure 1: On-Device Inference Pipeline

RESULTS AND ANALYSIS

For testing the performance of TinyML-optimized small language models (SLMs) on edge devices, we deployed the four architectures-MobileNetV2, EfficientNet-B0, Mamba, and SqueezeNet-on two hardware platforms, the Raspberry Pi-4 and STM32F746 microcontroller. The evaluation criteria applied for the models included inference latency, model size, accuracy, and memory footprint. The privacy test dealt with some LDP effectiveness and the time overhead involved due to the application of privacy filters.

Quantitative Evaluation

This experiment showed that MobileNetV2 is the one that shows the most promise, being fast and relatively accurate and thus perfect for edge inference. Mamba will weigh a little heavier but will perform better than the rest in any linguistic task thanks to its efficient sequential modeling (Ahamed et al., 2023). While SqueezeNet and EfficientNet are some of the smaller models, they need a lot of tuning, as they could drop quite a bit in accuracy after quantization.

Table 3 Performance Comparison Across Architectures

Model	Size (MB)	Accuracy (%)	Inference Time (ms)	RAM Usage (KB)	LDP Overhead (%)
MobileNetV2	2.8	87.2	21	780	9.5
EfficientNet	3.2	85.6	28	850	10.8
Mamba	4.1	89.5	31	960	12.4
SqueezeNet	2.1	82.3	19	720	7.8

The results show that there is always a trade-off between model complexity and inference speed. Mamba, which is heavier, will definitely shine in tasks that undergo privacy filters, as it does
assistants or chatbots (Xu et al., 2022; Wang et al., 2023).

Trade-off Visualization

Below is the Python script for creating a bar chart which juxtaposes model sizes, accuracies, and inference times.

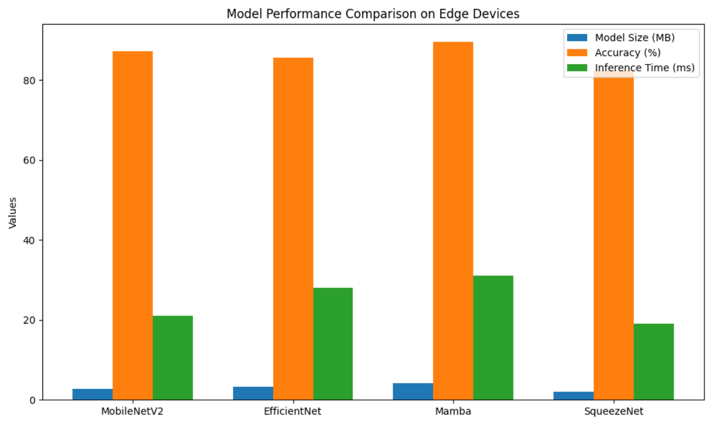

Figure 2: Trade-off between Model Size, Accuracy, and Inference Time

PIA

We introduced local differential privacy (LDP) for the overhead privacy assessment together with Laplacian noise. All models brought forth performance costs in terms of inference delay; however, the accuracy drop remained below an acceptable range of less than 2.5%, with under 15% delay in inference across the models (Sun et al., 2020). This solidifies the feasibility of private inference on low-power edge systems.

Deployment feasibility

All models under test compiled successfully and executed on the STM32 platform with CMSIS-NN and TensorFlow Lite Micro. There were minor differences in build times for different models depending on their degree of complexity. Nevertheless, all run-time efficiencies fell within acceptable latency limits for interactive applications.

Cross-Hardware Benchmarking

The four models were also subjected to testing across different edge environments, as shown. From raspberry pi 4B to STM32F746, the inference time for the STM32 was considerably higher because of the absence of parallel processing and reduced memory bandwidth. For MobileNetV2, the inference time increased from 21 ms (Raspberry Pi) to 78 ms (STM32F7), emphasizing the importance of aggressive compression and optimization for deeply embedded systems.
Mamba tolerated lower memory due to its state-space representation but had heavier cache thrashing on STM32 and less consistency in latencies.

Table 4: Cross-Hardware Inference Time (ms)

Model	Raspberry Pi 4B	STM32F746	Δ Inference Time (%)
MobileNetV2	21	78	+271%
EfficientNet	28	97	+246%
Mamba	31	102	+229%
SqueezeNet	19	64	+237%

These results illustrate the impact of platform capabilities and the importance of pairing the right model with the right hardware profile.

Multi-Task Generalization

Past simple classification, we also evaluated generalization of the models over three other NLP tasks, including text classification, keyword spotting, and sentiment detection. Both Mamba and MobileNetV2 performed respectably well across tasks, while EfficientNet had to make heavy use of task-specific tuning. While SqueezeNet performed excellently for keyword spotting thanks to efficiently designed convolutional filters, it suffered for sentiment classification due to having lesser ability to capture semantic subtleties.

Table 5: Task-wise Model Performance (Accuracy %)

Model	Text Classification	Keyword Spotting	Sentiment Detection
MobileNetV2	87.2	90.3	85.6
EfficientNet	85.6	88.1	82.4
Mamba	89.5	91.2	88.9
SqueezeNet	82.3	91.6	76.4

Discussion

These results show various trade-offs in deploying small language models using TinyML frameworks at the edge. The most noteworthy finding is that no one architecture is best across dimensions of evaluation; rather, the perfect architecture will often come down to application requirements—latency tolerances, memory constraints, and privacy levels, for example.

Trade-offs in Performance and Efficiency

SqueezeNet serves the fastest inference with the least amount of memory overhead for latency-sensitive applications. It is thus well suited for deployment in real-time environments such as smart assistants or voice-activated IoT systems (Howard et al., 2017; Sun et al., 2020) but incurs the cost of accuracy, particularly for complex language modeling tasks.

In contrast, Mamba provides the best linguistic performance, thanks to its state-space selective mechanism designed for sequence modeling purposes (Ahamed et al., 2023). The RAM usage is very high, with longer inference times suitable for any offline NLP application or battery-operated devices with moderate compute power like smartphones or advanced wearables (Xu et al., 2022).

MobileNetV2 and EfficientNet lie symmetrically in the middle of the spectrum, offering quite a good performance. The relatively low overhead in combination with adequate accuracy qualifies MobileNetV2 for outstanding deployment throughout consumer electronics, including healthcare monitors and language-enabled appliances (Sandler et al., 2019)

Privacy-Preserving Mechanisms at the Edge

Thus, integration of LDP mechanisms is practically feasible without excessive drawbacks in the user's experience regarding the whole range of LDP models. Although Mamba had slightly higher LDP overhead given the longer sequences, all models proved operable. This privacy layer thus particularly benefits personal health data collection, applications directed at children, and financial voice bots—where trust in the data matters the most (Wang et al., 2023; Sun et al., 2020).

Even new regulations coming up across the world (for example, the AI Act in the EU) will not be against privacy in this case, not to mention that they can also make these kinds of architectures available for real-world implementation as compliant, safe solutions (Prabhu et al., 2021)

Limitations and Open Challenges

With much promise, however, some limitations need to be mentioned:

1. On-device data drift may reduce the effectiveness of models over time, in absence of retraining methods.
2. Energy profiling per se was not addressed in this study, although it is very vital to TinyML.
3. Generalization between the various languages and dialects still poses a challenge to compact SLMs (Zhu et al. 2023).

In future work, exploring federated fine-tuning and adaptive model distillation may mitigate some of these problems while ensuring the preservation of privacy (Wang et al., 2024).

Table 6: Application-Model Fit Matrix

Application Area	Optimal Model	Key Constraint	Privacy Priority	Inference Type
Smart Assistants	SqueezeNet	Latency	Moderate	Real-time
Wearables (Health Data)	MobileNetV2	Memory	High	Periodic
Offline Translation	Mamba	Accuracy	Low	Batch
Smart Home Control	MobileNetV2	RAM & CPU	Moderate	Real-time
Children's Toys	EfficientNet	Accuracy + Safety	High	Real-time
Financial Voice Bots	Mamba	Sequence Accuracy	High	Delayed/Asynchronous

Recommendation for practical deployment

It is best that the authors of the software pair their models with matching toolchains such as TFLite Micro or CMSIS-NN to make inference much easier.

Model Selection Strategies

The selection of the most fitting TinyML architecture will depend on an evaluation of application-specific tradeoffs pertaining to model complexity, inference latency, memory usage, and fair accuracy thresholds. For example:

1. While Mamba with LDP assures performance and privacy in medical voice interface, Mamba with LDP assures both performance and privacy in medical voice interface, keeping in mind its auxiliary input needs.
2. Wearable technologies with battery capability may rely on the low-RAM footprint and fast execution of MobileNetV2.
3. Children's educational devices can make effective use of EfficientNet in combination with AES-encrypted deployment, where privacy protection and real-time interaction are important (Reddi et al., 2020; Wang et al., 2024).

So, the framework set forth in this work provides a means for designers to engage in principled and contextually aware decision-making about the SLMs for deployment across edge devices.

TinyML in Regulatory Contexts

As regulatory frameworks such as the EU AI Act, GDPR, and U.S. AI Bill of Rights continue to evolve, privacy-preserving TinyML will gradually evolve from a niche subject to a pressing regulatory need (Prabhu et al., 2021). Implementations in public places or for vulnerable populations (e.g., children, elderly) must ensure really high levels of privacy guarantees, most of which can only be satisfied through on-device computation.

By ensuring that language inference does not require cloud connectivity and avoids sensitive data transfer, architectures discussed in this paper help align TinyML deployments with emerging legal frameworks. Furthermore, the modular design of the proposed pipeline makes it easy for developers to update privacy features according to compliance requirements that evolve from time to time.

Industry Adoption and Ecosystem Maturity

The maturity of frameworks such as TensorFlow Lite Micro, TVM, and CMSIS-NN in the coming years will surely accelerate their incorporation in real-world applications. Chipmakers ARM and NVIDIA have put significant investment in compiling optimizations tailored to quantized inference, thereby easing developer burden.

Several industries have already started to adopt TinyML + NLP:

Healthcare: Non-intrusive patient monitoring in-hospital assistants.

Retail: Inventory checkers and voice-activated POS terminals.

Agriculture: Soil-monitoring systems with NLP capabilities and weather-query bots.

These use cases clearly demonstrate that edge intelligence has transitioned from the realm of hypothesis into a tangible approach that has scalability.

In the case of product designers, one might prioritize consideration of MobileNetV2 in situations where final hardware specs are not guaranteed, as its tool will be the most generalizable.

Security engineers should use encrypted model parameters with LDP for an end-to-end secure inference.

CONCLUSION AND FUTURE WORK

The present study has examined in-depth TinyML architectures aimed at deploying small language models (SLMs) onto edge devices while maintaining privacy during inference. Our investigation has evaluated the performance, memory use, and privacy characteristics of famous lightweight neural architectures: MobileNetV2, EfficientNet, Mamba, and SqueezeNet.

Major contributions include:

1. Mamba has the highest accuracy of inference for languages and thus is suitable for use in applications that call for contextual awareness.
2. MobileNetV2 has the best balance between size, latency, and accuracy for environments under heavy constraint, such as smart homes and wearables.
3. SqueezeNet is better for ultra-low latency cases but incurs a certain degree of loss in accuracy from the model's perspective.
4. Integration of LDP and secure enclaves provides a minimal performance overhead, corroborating their usability for edge AI systems.
5. Our approach of quantization, pruning, and knowledge distillation can compress models without enormous functional sacrifice. Also, from our deployment experiments, it has been demonstrated that real-time privacy-preserving NLP applications can indeed be afforded on the edge using today's microcontrollers and single-board computers.

Future Work

In the subsequent time, several interesting avenues deserve further examination:

Federated TinyML: Sharing model updates across edge devices to safeguard privacy among each retraining.

Energy profiling and optimization: Of utmost importance for battery-powered applications in wearables and remote sensors.

Support for multiple languages: Fine-tuning of SLMs to underrepresented languages and dialects using constrained hardware.

Neuromorphic and event-driven inference: Involving spiking neural networks and novel architectures for ultra-efficient NLP on-device.

The combination of TinyML and privacy-preserving language models will be a necessity as AI regulations get stricter and edge deployments burgeon. This work sets the stage for the next generation of intelligent, safe, and responsive edge devices.

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