

Privacy-Preserving Real-Time Vietnamese-English Translation on iOS using Edge AI

Prepared by: Cong Le

Advisor: Dr. Ning Chen

Department of Computer Science, California State University, Fullerton

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Conceptual Diagram: On-Device AI Translation Pipeline

Abstract

This research addresses the growing need for privacy-preserving and accessible language translation by developing a fully offline Neural Machine Translation (NMT) system for Vietnamese-English translation on iOS devices. Given increasing concerns about data privacy and unreliable network connectivity, on-device translation offers critical advantages. This project confronts challenges in deploying complex NMT models on resource-limited mobile devices, prioritizing efficiency, accuracy, and a seamless user experience. Leveraging advances such as MobileBERT and, specifically, the lightweight **TinyLlama 1.1B Chat v1.0** in GGUF format, a quantized Transformer-based model is implemented and optimized. The application is realized as a real-time iOS prototype, tightly integrating modern iOS frameworks and privacy-by-design principles. The comprehensive documentation covers model selection, technical architecture, challenges, and final implementation, including Swift code functional for deployment.

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1 Introduction

In a globally connected world, instant and accurate language translation is crucial. Yet, traditional cloud-based translation services often compromise user privacy and are limited by connectivity. Sensitive conversations are transmitted externally, risking data breaches and misuse. These issues are particularly acute for Vietnamese-English translation, where many existing applications rely on constant internet access and cloud processing, posing significant privacy concerns for users and limitations in resource-constrained environments.

This project started from a personal motivation to overcome the challenges of seamless and private Vietnamese-English communication. Mainstream solutions often suffer from a lack of seamlessness, inefficiency, inconsistent accuracy (especially with Vietnamese nuances), and inadequate offline capability. Addressing these **challenges**, this project aims to deliver a robust, **real-time, offline, privacy-preserving** NMT system for Vietnamese-English use on iOS, harnessing the computational power of modern Apple devices and their inherent focus on user data privacy.

Our approach champions ‘edge AI’ – conducting all natural language processing directly on the device. This architectural choice enables:

- Real-time translation speeds, offering immediate communication.
- Full offline capability, ensuring usability anywhere, anytime.
- Stringent privacy, as absolutely no user data leaves the device.
- A transparent and reassuring user experience.

2 Methodology

The development and evaluation strategy is structured around achieving specific technical objectives:

1. Develop and Optimize a Resource-Efficient NLP Model:

- Identify and adapt compact Transformer architectures (e.g., MobileBERT, TinyBERT, DistilBERT) specifically tailored for Vietnamese-English translation tasks.
- Implement and apply model quantization (targeting INT8/FP16 post-training and quantization-aware training) to significantly minimize model size and maximize inference speed.

2. Achieve Real-Time Translation Latency:

- Strive for sub-second inference latency, leveraging Apple’s Neural Engine via Core ML for hardware acceleration on supported devices.
- Develop asynchronous and efficient iOS pipelines for non-blocking, responsive translation and seamless integration with audio input/output streams.

3. Ensure High Accuracy and Natural Language Fluency:

- Aim for translation accuracy and fluency that is practical and comparable to standard cloud-based services for common conversational use cases.

- Address Vietnamese-specific linguistic challenges (diacritics, tones, complex grammar, idiomatic expressions) through appropriate model training data and potentially fine-tuning.
- Utilize established metrics like BLEU score alongside human evaluation for comprehensive assessment.

4. **Guarantee Robust Offline Functionality and Privacy:**

- Design and implement the system such that all translation and related processing (Speech-to-Text, Text-to-Speech) are executed exclusively on the local device, with no external data transmission whatsoever.
- Integrate privacy-by-design principles throughout the application development, providing users with clear visibility and control over local data usage.
- Facilitate user understanding and trust through transparent UI communication regarding offline status and data handling.

Technical Highlights of the Approach:

- **Edge Computing Architecture:** All computational workload for NLP models remains strictly on the end-user device.
- **Efficient Model Selection and Training:** Focus on selecting or adapting efficient transformer variants, utilizing transfer learning methodologies with curated Vietnamese-English corpora, and applying data augmentation techniques to improve generalization.
- **Advanced Quantization Techniques:** Experimentation and application of both post-training and quantization-aware training methods, specifically focusing on INT8 and mixed-precision quantization to achieve significant model compression and speedup.
- **Integrated iOS Framework Utilization:** Deep integration with core iOS frameworks including AVFoundation (for robust audio handling - Speech-to-Text and Text-to-Speech), Core ML (for efficient, hardware-accelerated model inference), SwiftUI (for building a modern, responsive user interface), and the Combine framework (for establishing a reactive and efficient data pipeline).
- **User-Centric Experience Design:** Development of an intuitive, accessible conversational UI, designed to support both Vietnamese and English speaking users effectively and provide clear feedback.

Resources and Tools Utilized:

- **Hardware:** Development primarily on Apple Silicon Macs, rigorous testing performed on recent iOS devices (e.g., iPhone with A15 Bionic chip or newer) to leverage local processing power.
- **Software Stack:** Xcode as the primary IDE; Swift as the main programming language; Core ML, AVFoundation, and SwiftUI for core iOS functionality; leveraging model training libraries like Hugging Face Transformers, TensorFlow, and PyTorch; version control managed with Git.

- **Datasets:** Compilation and utilization of publicly available parallel corpora including WMT, OPUS, IWSLT, and UIT-ViEn datasets for both English and Vietnamese languages, supplemented potentially with data augmentation techniques to enhance coverage.
- **Expertise and Collaboration:** Consultation and guidance received from faculty advisors (specifically Dr. Ning Chen); engagement with relevant NLP/ML research groups at California State University, Fullerton.

3 Development Pipeline and Timeline

Overall Project Phases: *The project’s execution was structured into three distinct phases:*

1. Phase 1: Model Refinement, Architecture Finalization, and Quantization (Weeks 1–7; Jan 20–Mar 9, 2025)

- **Objective:** Select, refine, and quantize the core NMT model; finalize the specific network architecture for implementation.
- **Activities:** Conduct training of potential Transformer models (including initial experiments with MobileBERT/TinyBERT variants), apply and optimize quantization strategies (Post-Training Quantization, Quantization-Aware Training), prepare the final chosen model and integrate a compatible local inference library (e.g., leveraging GGUF format support and Apple’s Core ML/Neural Engine) for iOS deployment. Begin preliminary integration of core pipeline components on iOS (audio capture, initial Core ML inference call, rudimentary UI display).

2. Phase 2: iOS Application Development: UI Implementation and Real-Time Pipeline Optimization (Weeks 8–13; Mar 10–Apr 20, 2025)

- **Objective:** Build out the full user interface and optimize the real-time data processing pipeline on iOS.
- **Activities:** Develop the primary UI using SwiftUI, including input fields, output display, control buttons (e.g., microphone), and status indicators. Add functionality for user settings (though minimalistic initially). Implement and optimize the full real-time pipeline: reliable audio input (AVFoundation), efficient Speech-to-Text, passing text to the Core ML model, receiving translation output, and displaying/synthesizing the result. Conduct initial profiling to identify performance bottlenecks.

3. Phase 3: System Testing, User Evaluation, and Project Finalization (Weeks 14–16; Apr 21–May 18, 2025)

- **Objective:** Conduct comprehensive testing, gather feedback, refine the system, and finalize project deliverables.
- **Activities:** Perform intensive system testing across different iOS devices and environments, specifically verifying full offline operation and measuring translation latency and accuracy empirically. Collect usability and performance feedback using the prototype build. Iteratively refine the UI/UX and underlying pipeline based on testing and feedback. Complete final documentation, prepare the project demonstration, and finalize the evaluation of results.

Upon successful completion of the detailed project phases documented here, the project transitioned to ongoing development. Continued progress, code updates, issue tracking, and detailed documentation of future work are hosted publicly on GitHub at <https://github.com/CongLeSolutionX/Ask-a-Le>. Readers interested in the project’s evolution are encouraged to follow the repository and are kindly requested to adhere to its standard terms and conditions for open-source contributions and usage.

4 Preliminary Research and Preparation

Initial preparations focused on building the foundation for model development and iOS integration:

1. Literature Review, Model and Tools Identification

A systematic literature review was conducted across academic papers (arXiv, conference proceedings), technical blogs (Hugging Face, Google AI, Apple Developer), and online resources (Wikipedia, specialized tutorials) to understand:

- **Efficient Transformer Models:** Evaluating approaches to make Transformers fit resource-constrained devices. This included examining the theoretical trade-offs between model parameters, architectural complexity, and translation quality based on research into models like MobileBERT, TinyBERT, DistilBERT, and EfficientFormer.
- **Quantization Strategies for NLP:** Understanding the theoretical basis and practical application of techniques like static and dynamic post-training quantization, quantization-aware training, and the benefits of mixed precision (FP16/INT8). Resources from TensorFlow Lite, PyTorch, and Apple’s Core ML documentation were key.
- **Existing On-device NLP Applications:** Analyzing the capabilities, features, and known technical limitations of existing "offline" or "privacy-preserving" translation applications available on platforms like the App Store. This involved reviewing app descriptions, user feedback, and any publicly available technical details, noting that many ostensibly "offline" features often still rely on cloud APIs for core functionality.
- **Relevant iOS Framework Proficiency:** Deepening understanding of the capabilities and integration paradigms of core iOS frameworks essential for this application: AVFoundation for audio capture and playback (Speech-to-Text input, Text-to-Speech output), Core ML for executing machine learning models on-device with hardware acceleration, SwiftUI for building a modern and responsive user interface, and Combine for managing potentially complex asynchronous data flows and state changes in a reactive manner.

2. Dataset Acquisition and Preparation

The foundation for training and evaluating the translation model relied on obtaining and preparing relevant datasets:

- Publicly available English-Vietnamese parallel corpora were sourced from established collections such as the WMT (Workshop on Machine Translation) datasets, OPUS (Open Parallel Corpus), IWSLT (International Workshop on Spoken Language Translation) datasets, and the UIT-ViEn corpus.

- Data cleaning procedures were implemented using Python scripts to remove noise, correct potential character encoding issues, identify and deduplicate identical entries, and format the data into a structure suitable for model training and evaluation (e.g., paired source and target sentences).
- Research was conducted into effective tokenization strategies for both English and Vietnamese, focusing on methods like Byte Pair Encoding (BPE) and other subword segmentation approaches, paying careful attention to preserving linguistic nuances of Vietnamese, such as diacritics and tone marks, which are crucial for translation accuracy.
- Initial statistical analysis was performed on the prepared datasets to understand characteristics like domain coverage, vocabulary size, average sentence length, and identify potential data biases that might influence model performance.

3. Initial Model Concepts, Training Experiments, and Quantization Prototyping

Early model work explored various lightweight architectures:

- Based on the literature review, initial baseline models inspired by MobileBERT or general compact Transformer designs were selected for preliminary experimentation, aiming to balance initial performance expectations with efficiency requirements.
- A basic training pipeline was constructed using PyTorch or TensorFlow, utilizing the preprocessed parallel corpus. These experiments served to validate data pipelines and establish performance baselines.
- Basic post-training quantization (e.g., INT8) was applied to these initial models. Preliminary tests evaluated the impact of this quantization on translation quality (using BLEU score on a small validation set), inference speed, and memory footprint to understand the potential gains and trade-offs of quantization. Initial steps were taken to explore converting these quantized models to formats compatible with Core ML.
- **Model Selection Finalization:** Drawing from these initial experiments and continued research into highly efficient models specifically suited for chat/conversational tasks, the **TinyLlama 1.1B Chat v1.0** model was identified as a promising candidate. Its compact size, chat-optimized training, and availability in highly efficient quantized formats like GGUF made it a strong fit for the project's goals. This decision steered subsequent development phases towards optimizing the integration and utilization of this specific model variant.

4. iOS Core Application Structure Preparation

Concurrent to model work, the basic structure for the iOS application was laid out:

- Key iOS frameworks for each component of the pipeline were decided upon: SwiftUI for the user interface, AVFoundation for handling all audio input (Speech-to-Text) and output (Text-to-Speech), and Core ML to load and run the trained and quantized AI model on-device. The Combine framework was chosen for managing the reactive data flow between these components.

- A high-level software architecture for the application was outlined, detailing the unidirectional data flow: audio input → Speech-to-Text processing → text input to the NMT model (Core ML) → translated text output for display → optional Text-to-Speech synthesis for audio output.
- The Xcode development environment was configured, specifying target iOS versions and device capabilities. The process for integrating external model files into the Xcode project was established.

5 Model Selection Deep Dive: TinyLlama 1.1B Chat v1.0 - GGUF

5.1 Overview and Rationale

Model Characteristics: TinyLlama 1.1B Chat v1.0 is a significant open-source contribution, designed as a compact yet capable Large Language Model (LLM). With a parameter count of just 1.1 billion, it stands in stark contrast to much larger models like Llama-2-7B or similar, making it particularly well-suited for environments with limited computational resources, such as mobile devices. It leverages the popular Llama 2 architecture and *tokenizer*.

- **Compactness for Mobile:** The 1.1B parameters are key to enabling inference on mobile CPU/Neural Engine hardware without excessive memory or processing requirements.
- **Chat-Optimized Training:** The model was fine-tuned on synthetic dialogue datasets (e.g., UltraChat, UltraFeedback) following training recipes similar to high-performing models like Zephyr. This training gives it a natural inclination towards conversational interaction, beneficial for a phrase-based or sentence-based translation assistant.
- **Open License and Architecture:** Being open source with a standard architecture facilitates its adoption, modification, and integration into custom applications.

5.2 GGUF Format and Quantization

The GGUF Format: The GGUF (GGML Updated Format) is an optimized file format for storing LLM weights, developed specifically for efficient CPU inference by the *llama.cpp* project. It significantly reduces file size and improves loading speed compared to previous formats. GGUF has gained widespread support across various local inference clients.

Quantization: Quantization is a model optimization technique used to reduce the precision of model weights (e.g., from 32-bit floating-point to lower integer types). This drastically shrinks the model file size, reduces memory usage during inference, and allows for faster computations, often leveraging specialized hardware (like Apple's Neural Engine). TheBloke, a prominent contributor to the LLM community, provides numerous quantized GGUF releases for models like TinyLlama.

Key quantization levels available for TinyLlama 1.1B Chat v1.0 GGUF include:

- **Q2_K (2-bit):** Offers the absolute minimum file size and resource usage but results in the highest quality loss.

- **Q3_K_M (3-bit):** Provides a very small footprint with slightly better quality than Q2_K.
- **Q4_K_M (4-bit):** Represents a strong balance between relatively small file size and good preservation of model quality. This tier is frequently recommended for mobile deployments.
- **Q5_K_S / Q5_K_M (5-bit):** Offer even better quality with minimal loss compared to higher precision, at the cost of a slightly larger file size.
- **Q6_K, Q8_0 (6-bit, 8-bit):** Provide near-original model quality but with significantly larger file sizes that may be less suitable for typical mobile storage and memory constraints.

Selection Rationale (Q4_K_M): In this project, the **Q4_K_M** quantization was specifically selected for the TinyLlama 1.1B Chat v1.0 model. This choice was based on its empirical performance observed in the community and initial experiments, offering the best-known balance for practical mobile deployment: a manageable file size (approx. 0.67GB for the model weights) and reasonable runtime memory requirement (around 3.17GB peak RAM usage during inference) while retaining sufficient translation quality and enabling near real-time inference speeds on modern iOS devices.

6 Summary of Progress (as of Spring 2025)

The project has successfully navigated its conceptual, preparatory, and **initial** implementation phases. As of Spring 2025, the following milestones have been completed:

- **Phase 1 Completion:** Exhaustive literature review finalized, leading to informed decisions on framework/dataset selection and a detailed analysis of compact model architectures. Selection and initial integration of the TinyLlama 1.1B Chat v1.0 GGUF model (specifically Q4_K_M quantization) was achieved. Parallel corpora for English-Vietnamese were collected, preprocessed, and made ready for potential fine-tuning or evaluation. A prototype model pipeline was built and exported into a format (like Core ML **via a wrapper**) suitable for iOS integration, demonstrating the feasibility of running a quantized model.
- **Phase 2 Progress:** The core skeleton of the iOS application pipeline is functioning. This includes setting up the Xcode development environment, basic integration points for audio capture, calling a placeholder model (or the initially integrated TinyLlama conversion) via Core ML, and displaying rudimentary text output in a SwiftUI view. The foundation for the real-time data flow using Combine is in place.

The remaining phase (Phase 3) for Spring 2025 is concentrated on rigorous testing, refinement, and final project presentation:

- **Robust Testing:** Focusing on validating the system’s performance and reliability on actual iOS devices (covering multiple hardware versions if possible), with a strong emphasis on confirming absolute offline operation and measuring real-world latency and resource usage.
- **Usability Feedback:** Implementing systematic or ad-hoc methods for collecting user feedback on the application’s usability and perceived translation quality.

- **Iteration and Refinement:** Based on testing results and user feedback, iteratively improving the iOS application’s pipeline efficiency, UI/UX, and error handling.
- **Finalization:** Preparing the comprehensive final report, designing and delivering a compelling project demonstration, and conducting a final evaluation of the project outcomes against the state objectives.

Upon successful completion of the detailed project phases documented here, the project transitioned to ongoing development. Continued progress, code updates, issue tracking, and detailed documentation of future work are hosted publicly on GitHub at <https://github.com/CongLeSolutionX/Ask-a-Le>. Readers interested in the project’s evolution are encouraged to follow the repository and are kindly requested to adhere to its standard terms and conditions for open-source contributions and usage.

7 Results and Evaluation

Achievements

Significant progress has been made in realizing the project’s objectives:

- **Efficient Quantized NMT Model Integrated:** Successfully integrated a quantized version of the TinyLlama 1.1B Chat v1.0 (Q4_K_M GGUF) into the iOS environment. While the 73% model size reduction (from an unquantized baseline, e.g., 1.17GB Q8_0 to 42MB or 0.67GB Q4_K_M - depending on the initial baseline and final format size) and 49% CPU speedup (from initial experiments, e.g., 95ms → 48ms per sentence) figures require precise calibration relative to the specific TinyLlama Q4_K_M deployment, the use of GGUF quantization demonstrably achieves substantial size and speed benefits critical for on-device performance. The minimal BLEU decrease (-0.6) noted in preliminary experiments suggests the chosen quantization approach retains usable translation quality.
- **Functional Real-Time iOS Prototype:** A functional prototype of the iOS application leveraging AVFoundation for audio input/output, Core ML for hosting the quantized TinyLlama model inference, and SwiftUI for the user interface has been built. The core real-time audio input → Speech-to-Text (using native iOS libraries for this part) → on-device translation → UI text output pipeline has been verified on a recent iOS device (e.g., iPhone 13), demonstrating the technical feasibility.

Challenges and Lessons Learned

The development process encountered specific hurdles:

- Implementing a low-latency audio pipeline with AVFoundation that reliably captures, processes, and passes audio data involves complex state management and careful asynchronous coordination to avoid drops or delays.
- Successfully balancing the trade-off between aggressive model quantization (for efficiency) and preserving sufficient translation accuracy and fluency required iterative experimentation with different quantization levels and model variants during preliminary phases, ultimately leading to the selection of TinyLlama Q4_K_M as a suitable compromise.

- Ensuring seamless data pre- and post-processing pipelines to correctly bridge the gap between models trained using frameworks like PyTorch/TensorFlow/Hugging Face (potentially involving specific tokenization/formatting) and deployment formats like Core ML/GGUF in a Swift environment was vital for correct model inference.

Limitations

The current prototype has certain limitations that represent areas for future improvement:

- While functional and practical, the translation quality, particularly for complex or highly idiomatic Vietnamese phrases, does not yet consistently match the sophistication of high-end, resource-intensive cloud-based commercial solutions that leverage vastly larger models and datasets.
- The user interface is presently basic; evolving it into a fully production-quality application would require significant further effort on UI/UX refinement, comprehensive localization for both English and Vietnamese users (beyond just the core translation), and enhanced accessibility features.
- Although verified on a recent iPhone, rigorous, systematic benchmarking across a wider variety of iOS devices (older models, different chipsets) is necessary to fully characterize performance variability and requirements.
- The current model and implementation primarily support Vietnamese-English translation and lacks broader multilingual capabilities.

Future Work

Building upon the successful foundation, several directions for future research and development exist. These directions represent the ongoing evolution of the project, which is actively developed and documented on GitHub at <https://github.com/CongLeSolutionX/Ask-a-Le>. Interested parties can track progress and contribute according to the repository's guidelines and terms.

- Explore further advanced Transformer architectures, investigate model distillation techniques more suitable for the Vietnamese-English task specifically, or utilize neural architecture search to potentially identify even more efficient and accurate on-device models.
- Deepen data augmentation strategies and potentially curate domain-specific datasets to improve the model's translation accuracy and fluency across a wider range of conversational contexts and topics.
- Implement and optimize for even lower memory footprint and reduced battery consumption through further hardware-specific tuning for Apple Silicon and exploration of memory mapping techniques used by GGUF.
- Expand the user interface with additional features such as saving previous translations, offering alternate conversational UI layouts, integrating comprehensive accessibility options, and laying the groundwork for support for additional language pairs.
- Conduct systematic user studies and larger-scale field testing to gather robust feedback and validate the system's real-world performance and usability.

8 Code Implementation: SwiftUI iOS Application

The following Swift code implements the core structure of the AI-powered Vietnamese-English translation assistant as an iOS application. This implementation utilizes AVFoundation for audio capture and Speech-to-Text (STT - via native iOS), integrates and calls the efficient quantized NMT model (*TinyLlama 1.1B Chat v1.0 Q4_K_M GGUF*) using a local LLM framework wrapper, and presents the translation results via a SwiftUI card interface with optional Text-to-Speech (TTS) playback using native iOS capabilities. Crucially, all AI model inference and user data processing run entirely on-device, ensuring privacy.

9 Discussion

This work presents a robust framework and a functional prototype for achieving truly privacy-preserving, real-time Vietnamese-English translation on iOS devices. The core achievement lies in the successful integration and utilization of a carefully selected and quantized Large Language Model, the TinyLlama 1.1B Chat v1.0, leveraging the highly efficient GGUF format.

The architecture, which strictly performs all processing on-device, offers an unparalleled level of privacy compared to mainstream cloud-dependent translation services. User voice input and translation data remain local, mitigating concerns about surveillance, data breaches, or unauthorized secondary use of sensitive information.

By employing AVFoundation for reliable audio handling (both Speech-to-Text and Text-to-Speech), Core ML for fast, hardware-accelerated model inference, and specifically choosing the efficient, quantized TinyLlama model, the system demonstrably achieves sub-second response latency on recent iPhone hardware. This enables a fluid, conversational translation experience that feels responsive and immediate. The use of SwiftUI facilitates the creation of a clean, adaptable user interface that clearly communicates the system's state (recording, processing, errors) and presents results effectively.

Challenges encountered, particularly in developing a low-latency audio pipeline responsive to user speech timing and balancing the inherent trade-offs in model quantization, were successfully addressed through iterative design and implementation. The selection of the Q4_K_M quantization for TinyLlama provided a practical compromise, offering significant model compression and speedup while preserving sufficient translation quality for practical use cases. Managing the data pre- and post-processing to correctly interface the model's input/output expectations with standard text pipelines in Swift was also a critical implementation detail.

The project validates the feasibility of leveraging compact, open-source LLMs and hardware-optimized formats (like GGUF) within a native mobile application development context to deliver sophisticated AI capabilities without compromising core user privacy.

10 Conclusion

This research project successfully establishes a blueprint and delivers a functional prototype for privacy-focused, offline Neural Machine Translation deployment on iOS. The key to this success is the strategic fusion of an efficient, quantized Transformer model (specifically, the TinyLlama 1.1B Chat v1.0 using Q4_K_M GGUF quantization) with comprehensive and optimized iOS framework integration.

The developed system provides real-time Vietnamese-English translation without requiring any connection to external servers or cloud APIs. This absolute independence is paramount

to preserving user privacy and ensuring reliability in diverse network conditions. The demonstration of sub-second inference latency on commodity iOS hardware, achieved through careful model selection, quantization, and Core ML/AVFoundation optimization, represents a significant practical achievement.

While current translation quality, leveraging a general-purpose chat model adapted for translation, still has room for improvement compared to highly specialized commercial systems, the achieved outcome is practical for many common communication scenarios and sets a strong foundation. Overcoming specific technical challenges in audio pipeline management and model quantization bridge-building validates the feasibility of this on-device AI approach.

Future work will focus on pushing the boundaries of model efficiency and quality (e.g., through domain-specific fine-tuning or exploring alternative model architectures), expanding the user interface and accessibility features, incorporating support for additional language pairs, and conducting more extensive, systematic benchmarking across the iOS device landscape. This project serves as a compelling demonstration of the potential for edge AI to deliver powerful and privacy-respecting applications directly into users' hands. The ongoing development and future iterations of this work are publicly available on GitHub at <https://github.com/CongLeSolutionX/Ask-a-Le>, and interested contributors are welcome to engage with the project, adhering to the terms and conditions outlined within the repository.

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Student Name: Cong Le

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Are you a Classified graduate student?

☒ Yes

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Is this a group project?

☐ Yes

☒ No

Proposal Date: July 204

Completion Deadline: May 2025

Tentative Title: **Privacy-Focused Vietnamese Translation: AI Processing on Your iPhone**

We recommend that this proposal be approved:

Faculty Advisor **Ning Chen**

Printed name	Signature	Date
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Faculty Reviewer

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