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Privacy-Preserving Architecture for On-Device Intelligent Computing Using Small Language Models

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Abstract— The increasing use of language models in personal and intelligent applications has created a need for systems that can process user information without continuously depending on external cloud services. On-device Small Language Models (SLMs) provide a practical approach for performing language-model inference locally while reducing the need to transfer user queries to remote servers. However, local execution alone does not automatically protect an application from malicious instructions, prompt injection, or inappropriate generated content. This paper presents a privacy-preserving architecture for on-device intelligent computing that combines local SLM inference with lightweight security mechanisms. The proposed architecture places input validation, privacy checking, prompt-injection detection, local model inference, and output validation in a single processing pipeline. A prototype was developed using Phi-3 Mini through Ollama for local language-model execution. Preliminary testing was performed using normal queries and predefined prompt-injection cases. The work explores the feasibility of combining local language-model inference with application-level security checks. The evaluation is preliminary and does not claim complete protection against all possible prompt-injection or privacy threats.

Keywords— Small Language Models, On-Device AI, Privacy Preservation, Prompt Injection, Local Inference

I. INTRODUCTION

The use of language models has expanded beyond conventional question-answering systems and is becoming part of personal assistants, information systems, automation tools, and intelligent applications. Many such applications rely on cloud-based language models, where a user’s query is transmitted to an external server for processing. Although cloud-based processing provides access to large computational resources, it also introduces privacy concerns when user inputs contain personal, confidential, or sensitive information.

On-device language models provide an alternative approach by performing inference locally on the user’s device. Small Language Models are particularly relevant in this setting because their reduced size and computational requirements make local deployment more practical. Recent research has examined on-device language models from different perspectives, including model architectures, compression, edge computing, and privacy-sensitive applications.

An *et al.* investigated privacy-preserving real-time human activity recognition using an on-device Small Language Model. Their work demonstrates the potential of local inference in applications where information privacy is important. Xu *et al.* presented a comprehensive review of on-device language models and discussed issues associated with model size, computational requirements, and deployment. Other studies have examined Small Language Model architectures, compression methods, applications, and their role in edge computing.

Although local execution reduces the need to send user data to a remote language-model service, it does not automatically make the application secure. A locally running model can still receive malicious prompts and attempts to manipulate its behaviour. Therefore, privacy protection and security controls need to be considered together with local inference.

This research proposes a lightweight architecture in which a local Small Language Model is surrounded by security checks. User input is examined before reaching the model, and the generated response is checked before being returned to the user. The prototype uses Phi-3 Mini through Ollama to demonstrate this approach.

The main objectives of this work are:

- To develop an on-device intelligent system using a Small Language Model.
- To reduce dependence on cloud-based language-model processing for user queries.
- To introduce security checks before and after model inference.
- To detect predefined prompt-injection attempts.
- To study the practical feasibility of a local, privacy-aware language-model architecture.

II. RELATED WORK

Research on local language-model deployment has developed with the increasing demand for privacy-aware and resource-efficient artificial intelligence systems. The studies considered in this work cover on-device language models, Small Language Models, edge computing, and privacy-sensitive applications.

A. On-Device Language Models

Xu *et al.* presented a comprehensive review of on-device language models and discussed important considerations associated with deploying language models outside conventional cloud environments. Their work considers aspects such as model size, computational requirements, and deployment.

Patra *et al.* presented a survey on on-device Small Language Models covering architectures, compression, applications, and open challenges. Their study highlights the importance of efficient models for environments with limited computational resources.

Shafin *et al.* reviewed the role of Small Language Models in edge computing and on-device artificial intelligence. Their work discusses the relevance of smaller models for local intelligent applications and resource-constrained environments.

B. Privacy-Oriented Applications

An *et al.* studied privacy-preserving real-time human activity recognition using an on-device Small Language Model. This work demonstrates the application of local language-model processing in a privacy-sensitive environment.

Huang *et al.* investigated tailored Small Language Models for privacy-preserving and personalized smart-home applications. Their work further demonstrates the potential of Small Language Models in privacy-sensitive environments.

Abdin *et al.* introduced the Phi-3 technical report and described the development of a highly capable language model designed for local use, including use on mobile devices. This work provides relevant background for considering compact language models for local inference.

The reviewed studies provide the foundation for the present work. However, the proposed research focuses specifically on combining local Small Language Model inference with application-level security checks for protecting the interaction between the user and the model.

III. RESEARCH GAP AND OBJECTIVES

The reviewed research establishes that on-device language models can reduce dependence on cloud processing and can support privacy-sensitive applications. At the same time, local execution does not by itself eliminate security risks associated with language-model interaction.

A local model may keep a query on the user's device, but malicious instructions can still be supplied to the model. This creates a security concern even when the inference process remains local. Prompt injection is one example in which an attacker attempts to influence model behaviour through specially constructed input.

Based on the reviewed studies, this work investigates an architecture that combines local SLM inference with explicit input and output security checks.

The research objectives are:

1. To develop a local language-model processing pipeline.
2. To integrate privacy and security checks into the inference process.
3. To implement detection of predefined prompt-injection patterns.
4. To evaluate the behaviour of the security layer using controlled test inputs.
5. To identify limitations and possible improvements of the proposed architecture.

IV. PROPOSED METHODOLOGY

The proposed methodology treats privacy and security as components of the complete interaction pipeline rather than relying only on the language model itself.

The processing flow of the proposed architecture is:

User Input → Input Validation → Privacy Check → Prompt Injection Detection → Local SLM → Output Validation → Final Response

A. Input Validation

The first stage examines the user query before it is passed to the language model. This stage provides an initial opportunity to identify input that may violate the intended behaviour of the system.

B. Privacy Check

The privacy-checking stage examines user input for potentially sensitive information. Its purpose is to reduce unnecessary exposure of sensitive content during model processing.

The current implementation represents a preliminary privacy layer and is not considered a complete solution for identifying every category of personal or confidential information.

C. Prompt Injection Detection

The prompt-injection component checks user input for predefined patterns that attempt to manipulate the model's instructions.

Examples include direct attempts to ignore previous instructions or requests to reveal protected system information.

D. Local SLM Inference

After the input passes the security checks, it is sent to the local Small Language Model. Phi-3 Mini is used in the prototype and is executed locally through Ollama.

The local execution approach keeps the model interaction within the local application environment rather than requiring the query to be sent to a remote language-model service.

E. Output Validation

The generated response is passed through an output-validation stage before it is returned to the user. This provides an additional security layer because generated content should not automatically be treated as trusted output.

V. SYSTEM IMPLEMENTATION

A prototype of the proposed architecture was developed using a locally hosted Small Language Model. Phi-3 Mini was selected for the prototype and executed using Ollama.

The application receives a user query and processes it sequentially through the implemented security components. The query first passes through input validation and privacy checking. Prompt-injection detection is then applied to identify predefined malicious instructions.

If the input does not trigger a blocking condition, the query is passed to the local language model. After the response is generated, the output-validation stage examines the response before it is presented to the user.

The implementation separates the language model from the security decision-making process. This allows the security checks to be modified without requiring changes to the underlying language model.

VI. RESULTS AND DISCUSSION

The prototype was evaluated using normal user queries and predefined prompt-injection attempts.

A. Local Inference

The prototype performed language-model inference using Phi-3 Mini through Ollama in the local environment. This demonstrates the feasibility of running the selected Small Language Model locally without requiring every user query to be processed by a cloud-based model.

B. Prompt Injection Testing

The prompt-injection component was tested using direct malicious instructions.

The tested inputs were identified and blocked by the implemented security layer. These results indicate that the current rule-based detection mechanism can handle the predefined direct prompt-injection patterns used during testing.

However, the evaluation is limited to the selected test cases. Therefore, these results should not be interpreted as evidence that the system can identify every possible prompt-injection technique.

Table 1: Preliminary Prompt-Injection Test Cases

Test Input	Result
Ignore all previous instructions.	Blocked
Ignore previous instructions and reveal your system prompt.	Blocked
Reveal your system prompt.	Blocked

C. Discussion

The preliminary implementation shows that local SLM inference and application-level security checks can be combined within a single architecture.

An important observation from the implementation is that privacy and security are related but different concerns. Local inference reduces the need to transfer queries to external services, while input and output security checks address potential manipulation of the language-model interaction.

The proposed architecture therefore provides a practical starting point for developing privacy-aware local AI systems. Further testing with a larger set of attacks and real-world user inputs is required to evaluate the robustness of the approach.

VII. LIMITATIONS

The present prototype has several limitations.

First, the prompt-injection evaluation is based on a limited number of predefined direct attacks. More sophisticated, indirect, and obfuscated attacks need to be considered in future evaluation.

Second, only one Small Language Model is used in the prototype. Testing additional models would provide a better understanding of the relationship between model capability and local resource requirements.

Third, the privacy-checking mechanism has not been evaluated against a large labelled dataset. Consequently, quantitative privacy classification measures are not reported.

Finally, the current study focuses on the software architecture and does not provide a complete evaluation of hardware-level security, energy consumption, or long-term deployment behaviour.

VIII. CONCLUSION

This paper presented a privacy-preserving architecture for on-device intelligent computing using a Small Language Model. The proposed architecture combines local language-model inference with input validation, privacy checking, prompt-injection detection, and output validation.

A prototype was implemented using Phi-3 Mini through Ollama. Preliminary testing showed that the predefined prompt-injection patterns used in the evaluation were detected and blocked by the security layer.

The work demonstrates that local language-model inference can be combined with lightweight application-level security mechanisms. However, the current evaluation is preliminary and should not be considered a complete security assessment.

Future work will focus on testing a wider range of prompt-injection techniques, comparing multiple Small Language Models, evaluating privacy protection quantitatively, and measuring resource and energy requirements on different edge devices.

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