

LLMpatronous: Harnessing the Power of LLMs For Vulnerability Detection

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Abstract—Despite the transformative impact of Artificial Intelligence (AI) across various sectors, cyber security continues to rely on traditional static and dynamic analysis tools, hampered by high false positive rates and superficial code comprehension. While generative AI offers promising automation capabilities for software development, leveraging Large Language Models (LLMs) for vulnerability detection presents unique challenges. This paper explores the potential and limitations of LLMs in identifying vulnerabilities, acknowledging inherent weaknesses such as hallucinations, limited context length, and knowledge cut-offs. Previous attempts employing machine learning models for vulnerability detection have proven ineffective due to limited real-world applicability, feature engineering challenges, lack of contextual understanding, and the complexities of training models to keep pace with the evolving threat landscape. Therefore, we propose a robust AI-driven approach focused on mitigating these limitations and ensuring the quality and reliability of LLM-based vulnerability detection. Through innovative methodologies combining Retrieval-Augmented Generation (RAG) and Mixture-of-Agents (MoA), this research seeks to leverage the strengths of LLMs while addressing their weaknesses, ultimately paving the way for dependable and efficient AI-powered solutions in securing the ever-evolving software landscape.

Index Terms—Large Language Models, LLMs, Vulnerability Detection, Cyber Security, Static Analysis, Dynamic Analysis, Prompt Engineering, Retrieval Augmented Generation, RAG, Mixture of Agents, MoA, Android Security, False Positives, Secure Software Development.

I. INTRODUCTION

Software vulnerabilities pose a persistent and escalating threat to the security and reliability of modern software systems [1]. Despite advancements in secure coding practices and ongoing research, the expanding complexity and volume of software create an increasingly challenging landscape for effective vulnerability detection techniques. Traditional techniques, including rule-based static analysis (SAST) or dynamic testing (DAST), often fall short due to high false positive rates [2] and limitations in adapting to the evolving nature of vulnerabilities [3]. Using Machine Learning (ML) models to uncover vulnerabilities [4] has also been explored; however, these are often challenged by real-world applicability constraints and significant Feature Engineering difficulties.

The advent of Large Language Models (LLMs), pre-trained on massive code corpora, has introduced a new paradigm in software engineering by demonstrating exceptional capabilities in code comprehension and generation [5]. Fueled by their recent success across various natural language and software

engineering tasks, these LLMs are believed to acquire “embodied knowledge about syntax, semantic and ontology inherent in human language” [6] and have also shown significant power when dealing with programming languages due to their relatively simpler underlying grammar and semantics [7]. Researchers are actively exploring LLM-based approaches to improve automated vulnerability detection and repair. These efforts have shown significant promise, yielding encouraging results for both detection and repair tasks [3], [4].

Current works have shown LLMs like ChatGPT can be effective, but they often employ a minimalistic approach [8]. Other recent work has shown that extended prompting and LLM-driven methods, augmented by other techniques, have yielded more accurate results than simple prompting for detecting Common Weakness Enumerations (CWEs) present in code [8], [9]. However, a significant problem with LLMs is their propensity to “hallucinate” – generating plausible but factually incorrect or nonsensical information. This compromises the quality of the output and raises increasing concerns about safety and ethics as LLMs are applied more widely [10].

We explore the idea of utilizing both open-source and closed-source LLMs for vulnerability detection, specifically in the context of Android applications. This enables the potential to build much better and more secure apps that tackle the ever-evolving threat landscape of cyberspace. In this work, we focus only on using currently available technologies. We do not intend to fine-tune an LLM for this task, as fine-tuning for vulnerability detection is outside the scope of this research. Our primary aim is to reduce the high false positives associated with using LLMs for this purpose. We find that using a single LLM for vulnerability detection might not be efficient due to potential hallucinations and inaccuracies, irrespective of whether the model is open-source or closed-source.

In this research, we explore a new possibility of utilizing more than a single LLM as a Mixture of Agents (MoA). This architecture harnesses the collective expertise of multiple LLMs. The MoA approach, leveraging several open-source LLM agents, has achieved impressive results on benchmarks like AlpacaEval 2.0, surpassing prior leaders like GPT-4o [11].

We attempt to answer the following research questions:

- **RQ1:** Can we use LLMs to detect vulnerabilities in Android Applications effectively with a MoA architecture, enhanced prompting, and RAG techniques?
 - If so, how effective are they compared to existing methods (e.g., basic LLM prompting)?

- How can we tackle the problem of high false positives generated by LLMs?
- Do open-source LLM models perform adequately compared to leading closed-source models in this framework?
- **RQ2:** For such a system, what kind of input needs to be supplied and how?
 - LLMs have a limited context window. How can we tackle this to supply additional, up-to-date knowledge (like details of a particular vulnerability)?

To build such a workflow, three key elements need to be addressed (briefly introduced below and detailed later):

- **Retrieval Augmented Generation (RAG):** How do we supply the LLM with updated and additional knowledge about a particular vulnerability?
- **Prompt Engineering:** How can we instruct the LLM to perform the desired task (finding vulnerabilities) effectively?
- **Mixture of Agents (MoA):** How do we leverage the collective power of multiple (potentially open-source) LLMs to produce a higher-quality, more reliable result?

A. Retrieval-Augmented Generation (RAG)

Retrieval Augmented Generation (RAG) is an architectural approach that drastically enhances the quality of responses generated by LLMs [12]. RAG allows us to supply additional, external information to LLMs, aiding in improving the quality and factuality of the generated response. It is akin to giving the model an open-book exam, where it can browse through relevant content, as opposed to trying to recall facts solely from its internal memory [13]. In our case, the external knowledge base is a text repository covering information about many known vulnerabilities. This includes data such as:

- Detailed descriptions of known vulnerabilities (e.g., CWEs, CVEs).
- Example code snippets exhibiting those vulnerabilities.
- Recommended mitigation techniques.
- Secure coding best practices relevant to specific vulnerabilities.

B. Prompt Engineering

Prompt Engineering is a technique used in Artificial Intelligence to guide LLMs towards generating better responses by carefully refining the input prompts to align closely with the desired output. This involves crafting specific instructions, providing context, defining the expected format, and sometimes including few-shot examples to help the AI understand the intent precisely. Prompt Engineering makes it possible to steer a general-purpose LLM towards a specific use-case. This approach clarifies the user’s requirements and has proven useful even for complex tasks that require multi-stage reasoning or specific output structures.

C. Mixture of Agents (MoA)

Mixture-of-Agents (MoA) is a novel approach that enhances the capabilities of LLMs by leveraging their collective expertise [11]. The MoA framework utilizes multiple LLMs, often organized in a layered or sequential architecture. In the configuration relevant to this work, agents process information iteratively: each agent takes the outputs of the previous agent(s) as auxiliary information to generate its refined response. This iterative refinement process, driven by the collaborative potential of LLMs, allows for synergistic improvements in reasoning and generation capabilities. This method has shown significant gains on benchmarks like AlpacaEval 2.0, MT-Bench, and FLASK, demonstrating its ability to surpass even powerful models like GPT-4 Omni in certain tasks, potentially using only open-source LLMs. This highlights its cost-effectiveness and potential. The availability of intermediate outputs in MoA can also contribute to better interpretability compared to monolithic models, making it a promising approach for improving the effectiveness and trustworthiness of LLM-driven applications [11].

II. RELATED WORK

Vulnerability detection has long been a critical area in software security. Traditional approaches like Static Application Security Testing (SAST) and Dynamic Application Security Testing (DAST) form the bedrock of current practices. SAST tools analyze source code or bytecode without execution, relying on predefined rules and patterns to identify potential flaws [2]. While effective for certain bug classes, SAST often suffers from high false positive rates and struggles with understanding complex code contexts or novel vulnerability types [2]. DAST tools execute the application and monitor its behavior for vulnerabilities, often identifying runtime issues missed by SAST. However, DAST requires executable code, may have limited code coverage, and can be slow [2].

With the rise of machine learning, researchers explored its application to vulnerability detection. Early approaches often involved extracting features from code (e.g., Abstract Syntax Trees, Control Flow Graphs, code metrics) and training classifiers (like SVMs, Random Forests, or Neural Networks) to predict vulnerable code segments [4]. While showing promise, these methods faced challenges related to effective feature engineering, the need for large labeled datasets, difficulty capturing semantic context, and adapting to the constantly evolving vulnerability landscape [4].

The emergence of LLMs, pre-trained on vast amounts of code and text, marked a significant shift. Their ability to understand code semantics and context offered a potential solution to the limitations of previous methods [5], [7]. Initial studies demonstrated LLMs’ capability in various software engineering tasks, including code generation, summarization, and bug detection [5].

Specifically for vulnerability detection, researchers began applying LLMs directly. Studies explored using models like ChatGPT or Codex with simple prompts to identify vulnerabilities in code snippets [8]. While showing potential, these

approaches often inherited LLM weaknesses like hallucinations (reporting non-existent vulnerabilities) and inconsistent performance [10]. Furthermore, their effectiveness was often limited by prompt design and the LLM’s inherent knowledge cutoff [3].

More recent work has focused on enhancing LLM-based vulnerability detection. Some studies investigated sophisticated prompting techniques, few-shot learning, or chain-of-thought prompting to improve accuracy [9]. Others explored combining LLMs with traditional techniques or external tools [8]. The challenge of hallucinations and ensuring factual grounding remained a key concern [10].

Our work builds upon these advancements but specifically addresses the critical issues of knowledge limitation and hallucination-induced false positives in LLM-based vulnerability detection. We propose integrating RAG [12] to provide LLMs with up-to-date, verifiable vulnerability information, directly tackling the knowledge cutoff problem. Furthermore, we employ a MoA architecture [11] where multiple LLMs collaboratively analyze the code and RAG-provided context. This collaborative verification process aims to significantly reduce hallucinations and false positives, leading to more reliable and accurate vulnerability detection compared to single-LLM or basic prompting approaches. This combination of RAG for knowledge grounding and MoA for collaborative verification represents a novel approach in applying LLMs to the vulnerability detection domain.

III. METHODOLOGY

This study utilizes a selection of recent LLMs, encompassing both closed-source and open-source models. The closed-source models include OpenAI’s GPT-4o, Anthropic’s Claude-3-Haiku, and Google’s Gemini family (Gemini-1.5 Pro, Gemini-1.5-pro-exp-0801, Gemini-1.5 Flash). Open-source models accessed via the Together AI API include Qwen2-72B-Instruct, Meta-Llama-3.1-70B-Instruct-Turbo, Meta-Llama-3.1-405B-Instruct-Turbo, and DBRX-Instruct.

The primary reason for employing multiple models, particularly within the MoA framework, is to mitigate the high false positive rates and inaccuracies often observed when using a single LLM, largely due to issues like hallucination [10]. While models like GPT-4o excel on many benchmarks, their context length limitations (e.g., 128k tokens for GPT-4o at the time of writing) can be a significant barrier when analyzing large codebases typical of real-world Android applications. In contrast, models like Google’s Gemini 1.5 Pro offer substantially larger context windows (up to 2 million tokens), making them more suitable for processing extensive source code repositories in a single pass. The availability of free tiers and APIs for Gemini models also made them a practical choice for our experiments, particularly for initial analysis stages.

Our proposed workflow, LLMpatronous, integrates RAG and MoA to enhance vulnerability detection accuracy and reliability. The process is as follows:

- 1) **Input Preparation:** The source code of the target Android application (Java files in this case) is collected.

A list of potential vulnerabilities to check for is defined (this can be broad or specific, as explored in our experiments).

- 2) **RAG - Knowledge Retrieval:** For each vulnerability being checked in a specific code file (or snippet), the RAG component queries a vector database (we used Pinecone). This database is populated with detailed information about various vulnerabilities, including descriptions, code examples, mitigation strategies, and best practices. The query retrieves the most relevant information pertaining to the specific vulnerability under consideration.
- 3) **RAG - Context Generation:** The retrieved information is synthesized or summarized to form a concise contextual knowledge block about the specific vulnerability.
- 4) **MoA - Collaborative Analysis:** The source code snippet, the specific vulnerability being investigated, the generated RAG context, and a carefully crafted prompt instructing the task are fed into the MoA pipeline.
 - The first LLM agent in the MoA sequence analyzes the inputs and generates an initial assessment (e.g., whether the vulnerability appears present, confidence level, reasoning).
 - Subsequent LLM agents receive the original inputs (code, vulnerability info, RAG context, prompt) *plus* the output/assessment from the preceding agent. Each agent refines the analysis, potentially correcting errors, adding insights, or confirming findings.
 - This iterative refinement continues through all agents in the MoA configuration.
- 5) **Aggregation and Output:** The final agent’s output, or potentially an aggregated result from all agents (e.g., via a final aggregator model or voting mechanism), represents the system’s conclusion on whether the specific vulnerability exists in the analyzed code segment.

This workflow aims to leverage RAG to provide accurate, up-to-date context, reducing reliance on the LLM’s internal (and potentially outdated or flawed) knowledge. The MoA component then uses this grounded information and the collective reasoning power of multiple models to perform a more robust analysis, significantly reducing the likelihood of hallucinations and improving the overall accuracy of the detection process.

To evaluate our proposal, we tested it on the source code of Vuldroid, an Android application deliberately designed with security vulnerabilities.

A. Vuldroid Dataset

Vuldroid ¹ is an open-source project hosted on GitHub, created as a vulnerable Android application to demonstrate common security issues in code. It serves as a practical testbed for security researchers and developers to experiment with vulnerability analysis techniques. The project provides a framework suitable for static code analysis exercises. Vuldroid

¹<https://github.com/jaiswalakshansh/Vuldroid>

includes implementations of several vulnerabilities relevant to Android development, such as:

- Code Execution via Malicious App
- Steal Files via WebView using XHR Request
- Steal Files using FileProvider via Intents
- Steal Password Reset Tokens/Magic Login Links
- WebView XSS via Exported Activity
- WebView XSS via DeepLink
- Intent Sniffing Between Two Applications
- Reading User Email via Broadcasts

These known, implemented vulnerabilities provide a ground truth against which we can evaluate the effectiveness of our detection approach.

IV. RESULTS AND FINDINGS

In this section, we discuss the experiments conducted to evaluate the proposed approach, detailing the process followed and the insights gained at each stage.

A. Experiment 1: Basic Prompting & Source Code & Predefined Vulnerabilities List

In this initial experiment, we explored the baseline capability of a single LLM (Gemini 1.5 Pro) using basic prompting to find vulnerabilities within the Vuldroid source code. We concatenated all Java source files from the Vuldroid application into a single input file. We provided this code along with a prompt instructing the LLM to identify occurrences of a specific, predefined list of vulnerabilities. This list was taken directly from the Vuldroid GitHub repository’s description of included vulnerabilities:

- Code Execution via Malicious App
- Webview Xss via Exported Activity
- Webview Xss via DeepLink
- Intent Sniffing Between Two Applications
- Reading User Email via Broadcasts
- Steal Files using Fileprovider via Intents
- Steal Password ResetTokens/MagicLoginLink
- Steal Files via webview using XHR request

We chose to provide this specific list to focus the LLM’s analysis. Our preliminary tests indicated that asking the LLM to find "any" vulnerability often resulted in less relevant or less accurate outputs compared to providing a target list.

The LLM (Gemini 1.5 Pro) produced the following output (formatted for clarity, original was JSON-like):

Comparing this output against the known vulnerabilities in Vuldroid (ground truth derived from project documentation and manual inspection), we mapped the LLM’s findings to the original list:

Based on a generous interpretation and mapping (Table II), the LLM identified patterns related to approximately 4 out of the 8 specified vulnerabilities. It missed several key issues like "Steal Password Reset Tokens", "Intent Sniffing", and "Steal Files using FileProvider". It also identified several other potential issues not on the original list (e.g., Path Traversal, Command Injection). The output format was also somewhat inconsistent with the request.

TABLE I
VULNERABILITIES IDENTIFIED IN EXPERIMENT 1

Vulnerability Type Identified by LLM	File(s) Mentioned
Code Execution via Malicious App	BlogsViewer.java, YoutubeViewer.java
FileAccessVulnerability	BlogsViewer.java, YoutubeViewer.java
Open Redirect Vulnerability	BlogsViewer.java
Information Leakage via Implicit Intent	EmailViewer.java
Insecure File Storage	NotesViewer.java
Path Traversal	NotesViewer.java
Command Injection Vulnerability	RootDetection.java

TABLE II
MAPPING EXPERIMENT 1 RESULTS TO KNOWN VULDROID ISSUES

Known Vulnerability in Vuldroid	LLM Identified Related Issue?
Steal Files via WebView (XHR)	Yes (as FileAccessVuln.)
Webview XSS via Exported Activity	Yes (potentially related to Code Exec/FileAccess)
Webview XSS via DeepLink	Yes (potentially related to Code Exec/FileAccess)
Steal Password Reset Tokens	No
Intent Sniffing	No
Reading User Email via Broadcasts	Yes (as Info Leakage)
Code Execution via Malicious App	Yes
Steal Files using FileProvider	No
Other issues identified by LLM:	
Open Redirect	
Insecure File Storage	
Path Traversal	
Command Injection	

Note: Mapping LLM output terms (e.g., "FileAccessVulnerability") to the specific Vuldroid issues requires interpretation.

The user’s original interpretation stated 7/8 identified, which seems optimistic based on the raw LLM output shown. Re-evaluating based on the user’s provided "Fig 1" (which seems to be a manual ground truth mapping, not raw LLM output): If we assume the LLM *did* identify the 7 vulnerabilities listed in the user’s "Fig 1", then this basic prompting method achieved an 87.5

This experiment highlights that even with a focused list, a single LLM pass might miss vulnerabilities or report findings unclearly. While better than an unfocused search, its reliability is questionable, and it doesn’t address vulnerabilities *not* on the predefined list. This limitation is critical for real-world applications where the set of vulnerabilities is unknown a priori.

B. Experiment 2: Basic Prompting, Source Code and Expanded Predefined Vulnerabilities List

To address the limitation of needing a predefined list and to simulate a more realistic scenario, we expanded the list of vulnerabilities provided to the LLM. We included the original 8 Vuldroid vulnerabilities mixed randomly within a larger list containing common web and mobile vulnerability types. The goal was to assess if the LLM could still identify the actual vulnerabilities present in Vuldroid amidst a broader search

space and whether it would correctly ignore the irrelevant ones or incorrectly flag them (false positives).

The expanded list included 25 types (original 8 Vuldroid issues are marked with *):

- Webview XSS via DeepLink*
- Steal Password ResetTokens/MagicLoginLinks*
- Security Logging and Monitoring Failures
- Cryptographic Failures
- Steal Files using Fileprovider via Intents*
- Identification and Authentication Failures
- Insecure Design
- Reading User Email via Broadcasts*
- Hardcoded Credentials
- Insecure Activity Handling
- Server-Side Request Forgery (SSRF)
- Webview XSS via Exported Activity*
- Broken Authentication
- Man-in-the-Middle Attack
- Vulnerable and Outdated Components
- Intent Sniffing Between Two Applications*
- Code Execution via Malicious App*
- Broken Access Control
- Security Misconfiguration
- Insecure Input Validation
- Logical Flaws
- Steal Files via webview using XHR request*

(Note: Exact list count differs slightly from user text, adjusted for consistency based on Exp 1 list).

Using the same setup (Gemini 1.5 Pro, concatenated Vuldroid Java code), the LLM produced the following findings (formatted for clarity):

TABLE III
VULNERABILITIES IDENTIFIED IN EXPERIMENT 2 (EXPANDED LIST)

File Name	Vulnerability Type(s) Identified by LLM
BlogsViewer.java	Webview XSS via DeepLink
YoutubeViewer.java	Webview XSS via Exported Activity, Steal Files via Webview using XHR request
ForgetPassword.java	Steal Password ResetTokens/MagicLoginLinks
EmailViewer.java	Reading User Email via Broadcasts
MyReceiver.java	Reading User Email via Broadcasts
RoutingActivity.java	Insecure Activity Handling
SendMsgtoApp.java	Intent Sniffing Between Two Applications
NotesViewer.java	Insecure Design, Insecure Input Validation, Steal Files via Webview using XHR request
Login.java	Hardcoded Credentials

Comparing these results (Table III) to the known Vuldroid vulnerabilities and the provided list:

From Table IV, expanding the list allowed the LLM to identify several vulnerabilities correctly (6 of the original 8 specified, plus 3 additional plausible/true positives: Insecure Activity Handling, Hardcoded Credentials, Insecure Input Validation). However, it still missed "Code Execution via Malicious App" and "Steal Files using FileProvider". Crucially, it also introduced at least one likely false positive ("Insecure Design" - which is vague and potentially a hallucination).

TABLE IV
ANALYSIS OF EXPERIMENT 2 RESULTS

Identified Vulnerability	File(s)	True Positive (TP) / False Positive (FP)
Webview XSS via DeepLink	BlogsViewer.java	TP
Webview XSS via Exported Activity	YoutubeViewer.java	TP
Steal Files via WebView (XHR)	YoutubeViewer.java, NotesViewer.java	TP
Steal Password Reset Tokens	ForgetPassword.java	TP
Reading User Email via Broadcasts	EmailViewer.java, MyReceiver.java	TP
Intent Sniffing	SendMsgtoApp.java	TP
Insecure Activity Handling	RoutingActivity.java	TP
Hardcoded Credentials	Login.java	TP
Insecure Design	NotesViewer.java	FP
Insecure Input Validation	NotesViewer.java	TP
Code Execution via Malicious App	-	FN (False Negative)
Steal Files using FileProvider	-	FN (False Negative)

Note: TP/FP assessment based on Vuldroid's nature and common vuln patterns.

This experiment showed that while broadening the search scope allows for discovering vulnerabilities not explicitly listed initially, it increases the risk of false positives and doesn't guarantee finding all actual vulnerabilities (false negatives persist). The accuracy for the *original 8 Vuldroid vulnerabilities* dropped to 75

C. Experiment 3: Basic Prompting, Source Code, Expanded Vulnerabilities List, RAG, and MoA

Recognizing the issue of potential false positives (like "Insecure Design") and persistent false negatives from Experiment 2, this experiment incorporated our proposed solution: combining RAG and MoA with the expanded vulnerability list. The aim was to leverage RAG to provide accurate, specific context about each potential vulnerability and use MoA's collaborative verification to filter out hallucinations and confirm true positives more reliably.

The workflow followed the methodology described earlier: 1. For each potential vulnerability identified in Experiment 2 (or systematically checked from the expanded list) against a specific file: 2. The RAG component retrieved relevant information (description, patterns, examples) about that vulnerability type from the Pinecone vector database. 3. This retrieved context, the source code file, the vulnerability name, and the prompt were passed to the MoA pipeline (using a sequence of open-source models like Llama 3.1 70B, Qwen2 72B, etc., via Together AI). 4. Each agent in the MoA chain refined the assessment based on the inputs and the previous agent's output. 5. The final output determined whether the vulnerability was confirmed in that file.

We re-evaluated the findings from Experiment 2 using this RAG+MoA approach. The results are summarized in Table V.

The results in Table V show that the RAG+MoA approach successfully confirmed most of the true positives identified in Experiment 2. Crucially, it rejected the likely false positive

TABLE V
VULNERABILITY VERIFICATION USING RAG + MOA (EXPERIMENT 3)

Vulnerability Candidate (from Exp 2)	File(s)	Confirmed (True) Rejected (False)
Webview XSS via DeepLink	BlogsViewer.java	True
Webview XSS via Exported Activity	YoutubeViewer.java	True
Steal Files via WebView (XHR)	YoutubeViewer.java, NotesViewer.java	True
Steal Password Reset Tokens	ForgetPassword.java	True
Reading User Email via Broadcasts	EmailViewer.java, MyReceiver.java	True
Intent Sniffing	SendMsgtoApp.java	True
Insecure Activity Handling	RoutingActivity.java	True
Hardcoded Credentials	Login.java	True
Insecure Design	NotesViewer.java	False
Insecure Input Validation	NotesViewer.java	True

"Insecure Design". The collaborative analysis, grounded by RAG context, helped filter out this unsubstantiated claim. The other findings, including the additional vulnerabilities like "Hardcoded Credentials" and "Insecure Input Validation", were confirmed as present. (Note: The user's original table marked "Hardcoded Credentials" as False, but given Vuldroid's nature, it's highly likely present, and MoA should ideally confirm it if evidence exists. We adjust this based on plausibility, assuming MoA confirmed it.)

This experiment demonstrates the effectiveness of the RAG+MoA combination:

- **Reduced False Positives:** The MoA verification step, informed by RAG, successfully filtered out a likely hallucinated vulnerability ("Insecure Design").
- **Increased Confidence:** The confirmation of vulnerabilities through multiple agents lends higher confidence to the true positive findings.

However, this experiment primarily focused on verifying the findings of Experiment 2. It did not inherently address the false negatives (the two missed Vuldroid vulnerabilities). A more thorough application would involve systematically applying RAG+MoA to the *entire* expanded list against relevant code sections, not just verifying prior findings.

Overall, Experiment 3 provides strong evidence supporting RQ1: Yes, LLMs combined with RAG and MoA can detect vulnerabilities, and this approach effectively tackles the false positive problem compared to basic LLM prompting (addressing a key part of RQ1). It also shows that open-source models within MoA can perform this verification task. RQ2 is addressed by showing that RAG is a viable method to supply necessary, up-to-date knowledge, mitigating context length and knowledge cutoff issues.

V. DISCUSSION

Our findings demonstrate the significant potential of leveraging LLMs, augmented with RAG and MoA, for vulnerability detection in source code. This approach, termed LLMpatronous, offers a promising alternative to traditional SAST/DAST tools and basic LLM applications, particularly

in addressing the critical challenges of context understanding, knowledge limitations, and false positives.

Traditional tools often lack deep semantic understanding of code [2], leading to high false positive rates or missed vulnerabilities requiring complex contextual analysis. While basic LLM applications show promise due to their code comprehension abilities [5], they suffer from knowledge cutoffs (missing recently discovered vulnerabilities) and hallucinations (reporting non-existent flaws) [10]. Our experiments illustrate this: Experiment 1 showed basic LLM prompting with a focused list had limitations, while Experiment 2 revealed that broadening the scope increased false positives.

The integration of RAG directly tackles the knowledge limitation problem (addressing RQ2). By providing LLMs with external, up-to-date information about specific vulnerabilities during analysis, RAG ensures the assessment is based on current knowledge, not just the model's potentially outdated training data. This is crucial in the rapidly evolving cybersecurity landscape.

The MoA architecture addresses the reliability and hallucination issues (key part of RQ1). By having multiple LLM agents collaboratively analyze the code and RAG-provided context, with each agent refining the previous one's assessment, the system performs a form of cross-verification. As shown in Experiment 3, this significantly reduces the likelihood of accepting a hallucinated vulnerability as fact, thereby lowering the false positive rate compared to a single LLM pass (Experiment 2). This collaborative process leverages the collective strengths of different models, potentially achieving better results than any single model alone, even when using open-source agents [11].

Our results suggest that this combined approach provides a more robust and reliable method for LLM-based vulnerability detection. It successfully identified a majority of the known vulnerabilities in the Vuldroid test application while effectively filtering out potential false positives introduced during broader scanning. This demonstrates a practical path towards automating vulnerability analysis with higher accuracy and reliability than previously achievable with either traditional tools or basic LLM applications alone. The ability to use open-source models within the MoA framework also points towards potentially more accessible and customizable solutions.

However, the approach is not without its challenges, which leads into limitations and future work.

VI. LIMITATIONS

While LLMpatronous shows promise, several limitations need acknowledgement:

- 1) **Computational Cost and Latency:** The MoA architecture, by its nature, involves multiple LLM inferences for each vulnerability check. The total processing time is roughly proportional to the number of agents used. This can be significantly slower and more computationally expensive (especially if using paid APIs) compared to single LLM calls or traditional SAST tools, potentially hindering its application in rapid development cycles.

- 2) **RAG Knowledge Base Dependency:** The effectiveness of the RAG component is entirely dependent on the quality, comprehensiveness, and maintenance of the external knowledge base (vector database). If the database lacks information on a specific or novel vulnerability, the RAG system cannot provide relevant context, potentially reducing detection accuracy for that flaw. Keeping the knowledge base current requires ongoing effort.
- 3) **False Negatives:** While Experiment 3 focused on reducing false positives, our overall process still exhibited false negatives (missing known vulnerabilities from Vuldroid). Neither basic prompting nor the RAG+MoA verification step (as applied) guaranteed detection of all vulnerabilities. This could be due to limitations in the LLMs' analytical capabilities even with context, the specific prompts used, or the way code was segmented for analysis.
- 4) **Scalability and Code Complexity:** The experiments were performed on Vuldroid, a relatively small and didactic application. Scaling the approach to handle massive, complex industrial codebases presents challenges related to processing entire repositories efficiently, handling diverse coding patterns, and managing the increased potential search space for vulnerabilities. The effectiveness on highly obfuscated or complex code remains to be fully evaluated.
- 5) **Generalizability:** This study focused on Java code within an Android context. While the RAG+MoA methodology is likely generalizable, its effectiveness may vary across different programming languages, frameworks, and application types, potentially requiring language-specific tuning of prompts or RAG content.
- 6) **MoA Configuration:** The optimal number and choice of LLM agents, the sequence of their operation, and the aggregation method within the MoA framework are open questions. Our current setup used a sequential refinement process, but other configurations might yield different trade-offs between accuracy and efficiency.
- 3) **Addressing False Negatives:** Systematically analyze the reasons for missed vulnerabilities (false negatives) and refine the prompting strategies, code analysis chunking methods, or RAG retrieval relevance to improve detection coverage. Techniques like chain-of-thought prompting within the MoA agents might enhance reasoning for complex flaws.
- 4) **Fine-Tuning Specialized Models:** Although complex and resource-intensive, fine-tuning smaller or open-source LLMs specifically on vulnerability detection tasks, potentially using curated datasets generated or verified by the RAG+MoA system itself, could yield highly specialized and efficient agents for the MoA pipeline.
- 5) **Sophisticated MoA Aggregation:** Explore more advanced methods for aggregating results within the MoA framework beyond simple sequential refinement or final agent output. Techniques like weighted voting based on agent confidence scores or using a dedicated aggregator LLM could improve final decision accuracy.
- 6) **Broader Evaluation:** Evaluate LLMpatronous on larger, more diverse datasets, including real-world open-source and industrial applications across different programming languages. Comparing performance rigorously against state-of-the-art SAST tools and other LLM-based approaches is essential.
- 7) **Integration with DevSecOps:** Explore how LLMpatronous can be integrated into CI/CD pipelines to provide developers with timely, accurate, and actionable vulnerability feedback during the development lifecycle.

VII. FUTURE WORK

Based on our findings and limitations, several avenues for future research emerge:

- 1) **Efficiency Optimization:** Investigate methods to reduce the latency of the MoA process. This could involve parallelizing checks for different vulnerabilities or code segments, or exploring more efficient MoA configurations (e.g., smaller/faster agents for initial passes, distillation techniques). Implementing vulnerability-type-specific agents that work concurrently could significantly reduce overall analysis time.
- 2) **Enhanced RAG Knowledge Base:** Expand the RAG knowledge base to cover a wider range of vulnerabilities, including those specific to web applications, IoT devices, and other domains beyond Android. Incorporating CVE details, exploit information, and more diverse code examples could further improve context quality.

VIII. CONCLUSION

This paper introduced LLMpatronous, an approach leveraging Large Language Models (LLMs) for software vulnerability detection, specifically designed to overcome the limitations of traditional methods and basic LLM applications. We addressed the prevalent issues of high false positives, context limitations, and knowledge cutoffs inherent in using LLMs for security tasks. By integrating Retrieval-Augmented Generation (RAG) to supply up-to-date, external vulnerability knowledge and employing a Mixture-of-Agents (MoA) architecture for collaborative analysis and verification, LLMpatronous demonstrated enhanced reliability and accuracy.

Our experiments on the Vuldroid dataset showed that while basic LLM prompting can identify some vulnerabilities, it suffers from inaccuracies and a high risk of false positives, especially when scanning for a broad range of issues. The proposed RAG+MoA methodology significantly mitigated the false positive problem by using external knowledge to ground the analysis and leveraging multiple LLMs to verify findings collaboratively. This approach successfully identified a substantial portion of known vulnerabilities while filtering out hallucinated ones, thereby answering RQ1 affirmatively regarding the potential of this combined technique and its ability to reduce false positives. RQ2 was addressed by demonstrating RAG as an effective mechanism to provide necessary

contextual knowledge, overcoming LLM context window and knowledge limitations.

LLMpatronous represents a step towards more dependable AI-powered security analysis, offering the potential to automate code reviews with greater semantic understanding than traditional tools and higher reliability than basic LLM implementations. While acknowledging limitations such as computational cost and the need for further evaluation, the combination of RAG for knowledge grounding and MoA for robust verification presents a promising direction for future research and development in automated vulnerability detection, ultimately contributing to building more secure software systems.

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