Fine-Tuning Multilingual Language Models for Code Review: An Empirical Study on Industrial C# Projects

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ABSTRACT

Code review is essential for maintaining software quality but often time-consuming and cognitively demanding, especially in industrial environments. Recent advancements in language models (LMs) have opened new avenues for automating core review tasks. This study presents the empirical evaluation of monolingual fine-tuning on the performance of open-source LMs across three key automated code review tasks: Code Change Quality Estimation, Review Comment Generation, and Code Refinement. We fine-tuned three distinct models-CodeReviewer, CodeLlama-7B, and DeepSeek-R1-Distill—on a C#-specific dataset combining public benchmarks with industrial repositories. Our study investigates how different configurations of programming languages and natural languages in the training data affect LM performance, particularly in comment generation. Additionally, we benchmark the fine-tuned models against an automated software analysis tool (ASAT) and human reviewers to evaluate their practical utility in real-world settings. Our results show that monolingual fine-tuning improves model accuracy and relevance compared to multilingual baselines. While LMs can effectively support code review workflows, especially for routine or repetitive tasks, human reviewers remain superior in handling semantically complex or context-sensitive changes. Our findings highlight the importance of language alignment and task-specific adaptation in optimizing LMs for automated code review.

KEYWORDS

Automated Code Review, Pretrained Language Models (PLMs), Large Language Models (LLMs), Automated Static Analysis Tools (ASATs), Human Evaluation, Software Engineering Automation

1 INTRODUCTION

Code review is a cornerstone of modern software engineering, serving multiple purposes including improving code quality, enforcing standards, detecting defects early, and promoting knowledge sharing across teams [10, 32, 58]. This systematic practice has evolved into an integral part of development workflows, functioning both as a quality assurance mechanism and as a collaborative tool for continuous improvement.

Beyond technical benefits, code reviews also serve a social function. By enabling developers to inspect each other's changes, they facilitate informal learning, especially for junior team members, and help maintain consistency in project-specific practices [62]. Additionally, they contribute to software maintainability and reduce the risk of costly bugs [3, 33, 43, 45].

Despite its numerous benefits, manual code review remains time-consuming, cognitively demanding, and difficult to scale effectively, particularly in large industrial projects [41, 53]. Developers spend approximately 3–6 hours per week on code review tasks [8]. In large projects, reviewer assignment delays can postpone approvals by up to 12 days [54]. The scale of this challenge is evident in major companies that process thousands of reviews monthly, with projects like Microsoft Bing handling approximately 3,000 reviews per month [45]. This demonstrates the substantial manual effort required and its potential to significantly impact development productivity.

Code review has undergone a significant transformation from traditional formal review approaches to today's collaborative, tool-supported methodologies [2, 8, 54]. Automated static analysis tools (ASATs) are commonly deployed to reduce manual reviewing efforts by automatically detecting code smells, bugs, and coding standard violations. However, these tools frequently exhibit high false-positive rates and lack the contextual understanding required for nuanced code evaluations [49, 59]. Consequently, developers must manually filter through numerous irrelevant warnings, which undermines tool effectiveness and user acceptance [24]. Current practices demonstrate significant effectiveness gaps, with only 15% of review comments indicating actual defects and up to 34.50% considered non-useful in major projects [25].

Recent developments in artificial intelligence (AI), particularly in deep learning and natural language processing (NLP), have sparked increasing interest in automating the code review process, commonly referred to as automated code review (ACR). These efforts are often driven by the use of language models (LMs)¹, which are trained to understand or generate natural language (NL) text. Various pretrained language models (PLMs) have been proposed to support ACR tasks, including generating review comments, suggesting improvements, and transforming code into reviewer-approved versions [53, 58, 62]. However, most of these efforts have focused

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¹We use the term Language Model (LM) to refer to any model trained to understand or generate textual data. A Pretrained Language Model (PLM) is an LM that has undergone a general-purpose pretraining phase on large-scale unlabeled data before being fine-tuned for specific downstream tasks. A Large Language Model (LLM) refers to an LM with a high number of parameters (often in the billions), enabling it to handle a wide range of tasks—either zero-shot or with minimal fine-tuning. An LLM can also be considered a PLM, but not all PLMs qualify as LLMs. We refer to the plural forms as LMs, PLMs, and LLMs, respectively, throughout this paper.

on monolingual models trained on a small set of dominant programming languages (PLs), such as Java and Python [26, 57], leaving their applicability to less represented languages like C# relatively underexplored. This leaves a notable research gap regarding the effectiveness of PLMs and LLMs for industrial-strength languages like C#, which, despite being widely used in enterprise software development, has received limited attention in prior ACR studies.

The emergence of large language models (LLMs) has further expanded the capabilities of ACR systems by enabling more context-aware and semantically rich interactions with code changes [29, 31]. These models can significantly reduce reviewers' manual workloads by automating repetitive tasks and identifying subtle issues that might otherwise go unnoticed. In some cases, organizations have already reported measurable improvements in review efficiency and developer satisfaction after integrating such models into their workflows [8]. Nonetheless, training LLMs for a specific language from scratch remains infeasible for most settings, as it requires large volumes of annotated data—which is costly and difficult to acquire for many PLs.

To address these challenges, some research has turned to multilingual PLMs pretrained on diverse PL corpora (codebases in multiple programming languages). These models have been explored in a range of software engineering tasks, including code summarization, search, and translation [1, 7]. However, they often demonstrate performance inconsistencies across languages—likely due to differences in syntax, idioms, and language-specific coding conventions, as well as the uneven representation of PLs in the pretraining datasets. This variability highlights the need for a language-aware adaptation, particularly for sensitive tasks like code review.

Further complicating this landscape, most prior evaluations have been conducted using open-source datasets drawn from platforms such as GitHub [25, 62]. While these datasets offer scale and accessibility, they may not accurately reflect the complexity, coding standards, and domain-specific practices of industrial software development.

Taken together, these observations highlight several underexplored areas: the limited applicability of LMs to C#, the lack of multitask evaluations, inconsistent comparisons across model types, and the limited availability of studies based on real-world, industrial code review data.

To overcome these limitations, we adopt a new approach by fine-tuning existing multilingual LMs on monolingual C# data. Specifically, we evaluate three open-source models with distinct pre-training objectives and architectural characteristics: CodeReviewer [26], a transformer-based encoder-decoder PLM designed specifically for review comment generation and pretrained on multilingual code corpora; CodeLlama-7B [47], a decoder-only multilingual LLM pretrained on a broad range of general-purpose code tasks; and DeepSeek-R1-Distill [15], a multilingual instruction-tuned LLM optimized for multi-domain applications.

To assess the effectiveness of these fine-tuned models in realistic review settings, we structure our evaluation around three core tasks commonly encountered in ACR workflows: (1) Code Change Quality Estimation [18, 26], which determines the necessity of human review for a given code change; (2) Review Comment Generation [25, 26, 29, 30, 57], where NL feedback is generated to guide developers; and (3) Code Refinement [23, 27, 28, 41, 53, 55], where

suggested improvements are automatically applied to the codebase. Due to computational resource constraints, we limited fine-tuning of CodeLlama-7B and DeepSeek-R1-Distill-Llama-8B to a single task. We selected Review Comment Generation, given its linguistic complexity and high practical relevance in real-world code review workflows. For each task, we compare the performance of the fine-tuned models against their original (non-fine-tuned) baselines to evaluate the added value of task-specific adaptation.

To systematically explore model performance across these tasks, we pose the following research questions: **RQ1**. Can fine-tuning a multilingual code review–specific PLM (CodeReviewer) on monolingual C# data improve its performance on Code Change Quality Estimation and Code Refinement? **RQ2**. How does fine-tuning different types of LMs—CodeReviewer, CodeLlama, and DeepSeek—on different PL/NL combinations affect Review Comment Generation? **RQ3**. How do fine-tuned LMs compare to an ASAT and human reviewers in identifying review-worthy code changes and generating feedback?

Our primary contributions are as follows:

- We conduct a systematic evaluation of three open-source LMs with distinct pretraining objectives (CodeReviewer, CodeLlama-7B, and DeepSeek-R1-Distill) fine-tuned on monolingual C# repositories across key ACR tasks.
- We analyze the impact of dataset language composition (English-only vs. mixed-language vs. multilingual) on model performance, demonstrating how aligning training data with the target review language improves review comment generation quality.
- We benchmark LMs against both an ASAT and human reviewers, providing a comprehensive assessment of their strengths and limitations across Code Change Quality Estimation, Review Comment Generation, and Code Refinement tasks.
- We offer detailed, task-specific insights into model behavior in real-world industrial C# development settings.

2 BACKGROUND AND RELATED WORK

2.1 Code Review Process

Modern code review is a collaborative quality assurance practice where developers evaluate proposed code changes before integration into the main codebase [2, 43]. Reviewers assess whether the submitted code satisfies both functional requirements (e.g., correct compilation and test coverage) and non-functional requirements such as readability, maintainability, and adherence to coding conventions.

The process typically involves analyzing source code written in a programming language (PL) and formulating feedback in natural language (NL). On platforms such as GitHub, Gerrit, and Phabricator, the review workflow follows five main steps. First, a contributor submits a patch through a pull request (PR). Then, one or more reviewers, ideally with relevant domain knowledge, examine the code diff and provide NL comments, along with approval or rejection votes. Based on this feedback, the contributor modifies the code. This review cycle iterates until the code meets predefined quality standards or the submission is discarded.

2.2 Automated Static Analysis Tools (ASATs) for Code Review

Manual code review remains a fundamental yet resource-intensive practice in software development. To reduce the manual effort required in this iterative process, a variety of automated approaches have been developed, with ASATs being among the earliest and most widely adopted solutions. ASATs enable developers to identify potential code issues—such as bugs, syntax violations, and deviations from best practices—without executing the code [9]. Widely used tools like SonarQube [50] and PMD [40] employ rule-based mechanisms to flag such issues early in the software development lifecycle, thereby supporting both quality assurance and coding standard enforcement.

Vassallo et al. [59] emphasize that successful integration of ASATs into developer workflows and trust in their outputs are key factors affecting their practical utility. Beller et al. [4] further observe that tool performance can vary depending on the PL, highlighting the role of contextual factors in tool effectiveness.

ASATs are particularly useful in identifying superficial defects such as style inconsistencies and common programming errors [34, 38, 49]. As reported by Singh et al. [49] report ASATs can automatically detect up to 16% of issues later identified by human reviewers, suggesting their potential to reduce reviewer workload. However, ASATs often struggle with more complex concerns—such as architectural or domain-specific flaws—and suffer from high false-positive rates that may lead to reviewer fatigue and declining trust [6].

While ASATs offer valuable support in code review by automating the detection of routine issues, their inability to address nuanced, context-dependent problems highlights the need for complementary solutions. To this end, our comparative evaluation includes SonarQube as a representative ASAT, selected for its strong performance baseline and widespread adoption in industry [21]. These limitations further motivate the investigation of more advanced approaches capable of handling the contextual and semantic complexity inherent in real-world code review scenarios.

2.3 Automated Code Review (ACR)

While ASATs help detect rule-based issues like style violations, simple bugs, and security vulnerabilities, they fall short in providing context-aware, semantic, or design-level feedback [18, 56, 58]. To address these limitations and reduce developers' cognitive load, the software engineering community has increasingly explored AI-driven and NLP-based solutions.

Early ACR research primarily focused on isolated quality aspects, including bug detection [32], vulnerability identification [5, 52], and style inconsistency detection [37], demonstrating positive effects on software maintainability [4, 38].

Building on these foundations, recent work in ACR has focused on three core tasks that collectively reflect the broader goals of the code review process.

The first is *Code Change Quality Estimation*, which aims to predict whether a given code change requires human review. Initial approaches relied on handcrafted features and shallow learning models [20], whereas more recent studies have employed deep

learning classifiers trained on semantic representations of code diffs to improve prediction accuracy [18, 22, 26].

The second is Review Comment Generation, widely considered the most linguistically and semantically demanding aspect of ACR. Unlike tasks such as code refinement, this task requires generating context-aware, human-like feedback based on limited code context. Task-specific PLMs, such as T5-Review [57], built on the T5 architecture [42] and trained on datasets like Stack Overflow and CodeSearchNet, often struggled to match the performance of refinement-focused models in generating high-quality comments. To improve the semantic alignment between code functionality and review comments, AUGER [25] introduced a joint modeling strategy that links code functionality with relevant review comments, leveraging pretraining techniques such as denoising and comment summarization to improve feedback relevance. Retrievalbased models like CommentFinder [19] further offered efficient, non-generative alternatives by surfacing relevant comments from historical data.

The third is *Code Refinement*, which focuses on automatically generating code changes in response to reviewer feedback. Models such as Trans-Review [58] applied sequence-to-sequence learning with source code abstraction [55] to reduce vocabulary size. Auto-Transform [53] improved identifier representation using Byte-Pair Encoding (BPE, a token compression technique) [48]. T5-Review [57] enhanced performance by leveraging large-scale code-text pretraining. Later methods, including CodeEditor [23] and D-ACT [41], focused on learning from code edits and diff-awareness.

Moving beyond isolated task formulations, recent research has explored multi-task learning and large-scale pretraining to support the entire code review pipeline. For instance, CCT5 [27] was trained on 1.5 million diff-comment pairs and designed to address both review comment generation and code refinement. Lin et al. [29] proposed experience-aware oversampling to emphasize high-quality human reviews, improving model performance across multiple review stages. A large-scale benchmark by Zhao et al. [62] systematically compared three task-specific PLMs (Trans-Review, AutoTransform, and T5-Review) with general-purpose code PLMs (CodeBERT [11], CodeT5 [61]) across all ACR tasks. Their findings showed that CodeT5 achieved the highest performance in code refinement, whereas T5-Review outperformed others in review comment generation, highlighting the advantages of task specialization for linguistically complex review tasks.

The emergence of LLMs has further broadened the scope of ACR. Lu et al. [31] presented LLaMA-Reviewer, which leverages LoRA (Low-Rank Adaptation), a parameter-efficient fine-tuning method that updates only a subset of model weights, to support all three ACR stages without full retraining. Guo et al. [16] found that ChatGPT, despite lacking task-specific fine-tuning, outperformed CodeReviewer in refinement tasks but underperformed in comment generation. Complementing these efforts, Cihan et al. [8] conducted one of the first in-situ evaluations of LLM-assisted code review in industry, reporting better comment resolution rates but mixed developer satisfaction and increased PR closure times.

Despite these advances, open-source LLMs continue to lag behind proprietary models trained on expert-curated industrial datasets [27, 60]. Moreover, comprehensive evaluations covering all three ACR stages remain limited—particularly in realistic, industry-grade

C# codebases and in direct comparisons with both ASAT and human reviewers. Recent works [16, 31] have started to examine the potential of general-purpose, instruction-tuned LLMs (e.g., Chat-GPT, DeepSeek-R1-Distill) for code review tasks. Instruction-tuned models are trained to interpret and follow NL instructions, enabling them to generate appropriate responses to user prompts without requiring task-specific fine-tuning. These models show promising performance in reasoning and comment relevance, despite lacking explicit code-specific pretraining. However, direct comparisons between code-pretrained and general-purpose LLMs in industrial C# settings remain scarce—highlighting a critical gap that this study aims to address. C# remains a widely used language in enterprise software development, particularly in sectors such as finance, energy, and manufacturing [36]. Despite its industry relevance, it remains underrepresented in academic datasets and ACR studies.

3 STUDY DESIGN AND METHODOLOGY

This section provides an overview of our experimental setup, including the environment, dataset construction, model fine-tuning, and evaluation framework. Figure 1 illustrates the overall workflow of our study.

3.1 Study Context

This study investigates the effectiveness of fine-tuning three different types of LMs on monolingual C# data across three code review tasks in an industrial setting. Our research is motivated by the performance gap observed between public benchmark results and real-world industrial deployments of LM-based ACR systems [13, 60].

We collaborated with Lovion GmbH, a software company specializing in end-to-end digital solutions for infrastructure asset and network management. Their development teams primarily work with C#, follow an agile methodology, and actively adopt the latest advancements in software engineering technologies.

Access to Lovion's internal repositories provided us with high-quality, production-grade review comments written by experienced engineers. This unique dataset allows us to evaluate LLM performance under realistic conditions and explore how training data language composition (English-only vs. multilingual vs. translated) affects review comment generation quality.

By focusing on C#, a PL with high industrial relevance [44], we aim to provide practical insights for both researchers and practitioners on adapting LMs for industrial ACR tasks.

3.2 Data Preparation

We built task-specific datasets by combining PRs and reviewer comments from five internal C# repositories at Lovion GmbH with samples from the CodeReviewer benchmark [26]. Data extraction from Lovion's repositories was conducted via Gitea's REST API, ensuring comprehensive metadata coverage, including PR information, code diffs, and review comments.

To ensure data quality, we removed duplicate PR entries and filtered out incomplete or non-compilable code snippets. Since Lovion's review comments were originally written in German, we translated them into English using machine translation to create a linguistically unified dataset compatible with the CodeReviewer

benchmark. To ensure translation fidelity and domain relevance, we manually reviewed a stratified sample of the translated comments.

For each of the three downstream tasks, we created dedicated datasets. Each was randomly split into training (85%), validation (7.5%), and test (7.5%) subsets. To mitigate ordering bias, all datasets were shuffled prior to splitting.

Finally, we applied task-specific data formatting. For Code Change Quality Estimation, we labeled each diff hunk as either requiring a review comment (y=1) or not (y=0), ensuring a balanced class distribution. Positive samples (y=1) were directly sourced from the Comment Generation dataset. Negative samples (y=0) were extracted from the final PR versions where no reviewer comments were issued for the corresponding diff hunks, indicating either reviewer approval or irrelevance. For Comment Generation, each instance included a code diff and its corresponding human-written review comment. For Code Refinement, each data point consisted of a before-and-after code pair reflecting reviewer-suggested changes.

An overview of the C# data preparation pipeline—including extraction, cleaning, merging, and task-specific formatting—is provided in Figure 2. Detailed dataset statistics across all tasks and sources are summarized in Table 1.

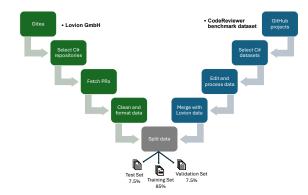


Figure 2: Dataset preparation workflow.

Table 1: Dataset statistics across three tasks and data sources.

Task	Dataset	Train	Val	Test
Code Change Quality Estimation	Lovion	19,110	1,685	1,686
	CodeReviewer	19,110	1,685	1,686
	Unified	38,220	3,370	3,372
Comment Generation	Lovion	3,420	302	302
	CodeReviewer	15,689	1,383	1,384
	Unified	19,110	1,685	1,686
Code Refinement	Lovion	2,125	187	188
	CodeReviewer	13,848	1,222	1,222
	Unified	15,973	1,409	1,410

3.3 Experimental Setup

We conducted all experiments on a GPU-accelerated server running Ubuntu 20.04, equipped with Python 3.12 and an NVIDIA A100 GPU

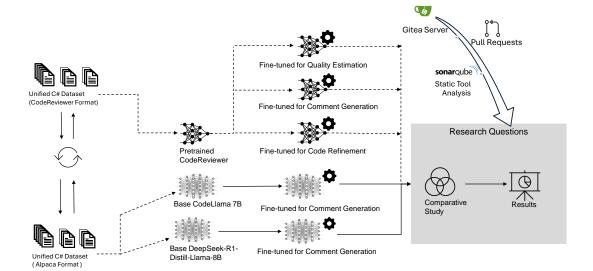


Figure 1: Overview of the experimental workflow.

(80 GB VRAM). For model development and fine-tuning, we used PyTorch 2.0 (CUDA 11.8) in combination with Hugging Face Transformers (v4.48). We implemented QLoRA (Quantized Low-Rank Adaptation) fine-tuning using the Axolotl and Unsloth frameworks. QLoRA enables efficient fine-tuning of large language models by combining parameter-efficient low-rank updates with quantization techniques that reduce memory usage. Additionally, we used NumPy and scikit-learn for data preprocessing and evaluation.

3.4 Model Fine-Tuning

We fine-tuned three distinct models in this study: CodeReviewer [26], CodeLlama-7B [46], and DeepSeek-R1-Distill-Llama-8B [15]. CodeReviewer is a transformer-based encoder-decoder PLM pretrained on multilingual code and review comment pairs. It was specifically developed for ACR tasks and thus represents a review-specialized PLM. CodeLlama-7B is a decoder-only LLM pretrained on a wide range of code corpora in multiple PLs. It serves as a code-pretrained LLM optimized for general code understanding and generation. DeepSeek-R1-Distill-Llama-8B is an instruction-tuned general-purpose LLM, distilled from LLaMA 3.1–8B, with no code-specific pretraining. It is designed to perform well across diverse NL tasks, including reasoning and instruction following.

This diversity in pretraining paradigms enables a comprehensive comparison of review-specific, code-oriented, and general-purpose LMs in realistic monolingual C# review settings.

Fine-Tuning CodeReviewer for Three ACR Tasks. We fine-tuned *CodeReviewer* for all three ACR tasks based on its original multi-task design and prior performance in both classification and generation tasks [26]. We followed the original implementation as a basis and adapted task-specific hyperparameters where needed.

(1) Code Change Quality Estimation: We fine-tuned CodeReviewer as a binary classifier to predict whether a code change requires a review comment (y = 1) or not (y = 0). Using a learning rate of 3×10^{-4} , we trained the model for

- 5 epochs with a batch size of 12. This configuration helped accelerate training while maintaining stability.
- (2) Review Comment Generation: We applied a two-stage fine-tuning approach. In the first stage, we used a mixed-language dataset that included German comments from the Lovion dataset and English comments from the CodeReviewer benchmark. In the second stage, we translated all German comments into English using Python's googletrans library [14] and retrained the model on a fully English dataset. Across both stages, the model was trained for approximately 3 epochs (around 7,500 steps) using a learning rate of 3 × 10⁻⁴ and a batch size of 6.
- (3) Code Refinement: For this task, we trained the model to generate improved code versions based on reviewer feedback. Fine-tuning was performed for 3-4 epochs using a batch size of 8 and a learning rate of 3×10^{-4} , striking a balance between efficiency and convergence.

Fine-Tuning CodeLlama and DeepSeek for Review Comment Generation. Given the linguistic complexity and practical relevance of the Review Comment Generation task, we fine-tuned both CodeLlama-7B and DeepSeek-R1-Distill-Llama-8B specifically for this purpose. Their instruction-tuned architectures and strong NL generation capabilities make them particularly well-suited for review comment generation. Due to computational constraints, we focused their evaluation exclusively on review comment generation to assess their ability to generate high-quality, context-aware review comments for C#.

To enable instruction-based fine-tuning, we reformatted the dataset using the Stanford Alpaca prompt format [51], in line with best practices for instruction-tuned LLM training [31]. Each prompt included (i) an instruction field describing the task (e.g., "Generate a review comment for the following code snippet"), (ii) an input field containing the code diff, and (iii) an output field with the

corresponding human-written review comment. The full prompt template is provided in Table 2.

Table 2: Instruction-based prompt format used for finetuning.

Prompt Template: Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.

###Instruction: {instruction}

###Input: {input}
###Response:{output}

Instruction

You are a powerful code reviewer model for the C#. Your job is to suggest review comment in natural language. You are given a context regarding a diff hunk or code change in programming language. You must output appropriate, contextual review comment for that code change.

Input: Diff Hunk: {diff hunk}
Output: {review comment}

We fine-tuned both models using 4-bit QLoRA, a technique that enables efficient fine-tuning of large-scale models by combining weight quantization with low-rank adaptation. The shared hyperparameters included 3 training epochs, a LoRA rank of 32 (i.e., the dimensionality of the trainable low-rank matrices), a token limit of 2,048, a dropout rate of 0.05, and a learning rate of 0.0002, optimized using the paged AdamW algorithm. For *CodeLlama-7B*, we employed the Axolotl framework with a weight decay of 0.0, whereas for *DeepSeek-R1-Distill-Llama-8B*, we used the Unsloth framework with a weight decay of 0.01.

Training Data Scope and Language Composition. Since both the programming language (PL) used in the code and the natural language (NL) used in review comments vary across models and datasets, we classified the training configurations along two dimensions:

• PL Scope:

- Mono-PL: Only C# code.
- Multi-PL: Multiple PLs (e.g., Java, Python, C#) from the multilingual benchmark [17, 26].

• NL of Comments:

- English-only: All comments translated and unified to English.
- English+German: Mixed comments in both languages.
- Multilingual: Diverse NL from the original multilingual benchmark.

All fine-tuning scripts, configuration files, and hyperparameter settings are publicly available in our replication package².

3.5 SonarQube Integration

SonarQube [50] is a widely adopted open-source ASAT that detects code quality issues across three primary dimensions: reliability, maintainability, and security. It identifies a variety of issues, including bugs, code smells, and security vulnerabilities. While

SonarQube's definition of code smells partially overlaps with the classic taxonomy introduced by Fowler [12], it also incorporates platform-specific classifications and rule extensions.

For this study, we configured SonarQube specifically for C# by activating approximately 450 language-specific rules from the official SonarC# rule set³. This ensured adherence to recognized best practices for C# development, covering security, reliability, and maintainability.

We used SonarQube as a rule-based baseline to evaluate the effectiveness of both LMs and human reviewers. Its outputs provided a reference point for identifying overlapping or missed issues across security, reliability, and maintainability dimensions. To integrate SonarQube into Lovion GmbH's DevOps pipeline, we deployed the system within the company's Jenkins-based continuous integration (CI) workflow (see Figure 3). This setup enabled automated analysis of all relevant PRs and ensured consistent quality assessment outputs. These outputs served as a static baseline against which we compared both LM-generated and human-written code review results.

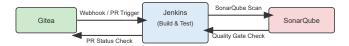


Figure 3: SonarQube integration in the Jenkins CI pipeline.

3.6 Evaluation Framework

Evaluation Scope. To evaluate the effect of fine-tuning, we included both fine-tuned and non-fine-tuned versions of each model in our experimental setup. Our evaluation combines both task-wide assessments over the full dataset and human-aligned evaluations conducted on a 40-PR subset. While BLEU and execution time metrics were computed across all PRs, human-centered evaluations (e.g., Information, Relevance) and comparisons to human reviewers or SonarQube were restricted to the manually annotated subset. This dual-scope approach ensures both large-scale comparability and in-depth quality benchmarking.

Evaluation Metrics. We adopted a multi-metric framework to assess both task-specific model outputs and overall code review effectiveness.

For *Code Change Quality Estimation*, we used standard classification metrics: accuracy, precision, recall, and F1 score.

For Review Comment Generation, we applied both:

- Automated evaluation: We used BLEU-4 [39] to measure lexical overlap between generated and reference comments. Following prior studies [26, 35], we computed BLEU scores over the first 256 tokens of each output. For DeepSeek-R1-Distill-Llama-8B, we excluded chain-of-thought (CoT) reasoning segments prior to scoring to ensure comparability with other models.
- Human evaluation: Six professional software engineers rated each AI-generated comment along two dimensions: Information (extent to which the comment provides meaningful and actionable feedback) and Relevance (degree to which

 $^{^2} https://github.com/DAP5555/code\text{-}review$

³https://rules.sonarsource.com/csharp/

the comment addresses the actual issue in the code diff). Both dimensions were rated on a 5-point Likert scale (1-5). The final score for each comment was calculated by averaging the six individual ratings.

For *Code Refinement*, we used BLEU to assess n-gram similarity and EM to check for byte-level equality between generated and reference code revisions.

For *Efficiency*, we measured the total time taken from receiving the input to producing the output. Human reviewers were timed manually, whereas the response times for LMs and SonarQube were extracted from system log files.

Dataset and Ground Truth. For human-aligned comparisons, we used 40 PRs sampled from Lovion GmbH's industrial C# repositories. Each PR included one code hunk to ensure alignment. Two senior engineers annotated whether a review comment was required and the associated issue category. Disagreements were resolved through discussion.

Evaluation Procedure. For the 40 PRs:

- In the Code Change Quality Estimation task, we compared LMs and SonarQube predictions against ground truth and human reviewer judgments (via majority vote).
- In the Review Comment Generation task, we evaluated the 20
 PRs labeled as requiring comments using BLEU and human
 scores, and further classified each comment as "good" or
 "not good" based on issue alignment.

Human Reviewer Baseline. We recruited six bilingual software engineers (2 senior, 2 mid-level, 2 junior) to (i) write review comments and (ii) rate model outputs. Their aggregated ratings served as a human baseline across all evaluation dimensions.

4 RESULTS

4.1 Results of Code Change Quality Estimation

Figure 4 shows the performance of CodeReviewer on the code change quality estimation task, comparing the monolingual C# fine-tuned variant with the multilingual baseline by Li et al. [26]. Despite being trained on a smaller dataset, the monolingual version outperformed the multilingual model across all evaluation metrics, including precision, recall, F1 score, and accuracy. This consistent improvement suggests that domain and language specific fine-tuning can effectively enhance the model's ability to identify relevant code changes, even with limited training data.

4.2 Results of Review Comment Generation

Table 3 provides a comparative evaluation of the models on the review comment generation task, using both automated (BLEU-4) and human-centered (Information and Relevance) metrics. A key finding is that no single model dominates across all evaluation criteria, indicating trade-offs between lexical similarity, informativeness, and contextual relevance.

CodeReviewer, when fine-tuned on monolingual C# with Englishonly comments, achieves the highest BLEU-4 score, reflecting strong alignment with reference phrasing. However, it slightly lags behind the base model in Information and Relevance. Its bilingual variant performs similarly in BLEU-4 but worse in human evaluations, suggesting that linguistic inconsistency in training data may reduce

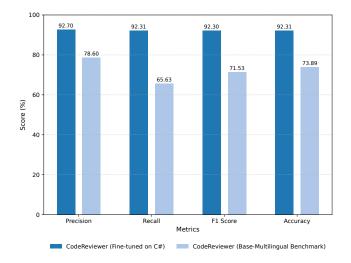


Figure 4: Code change quality estimation performance of CodeReviewer fine-tuned on monolingual C# data compared to its base multilingual version.

fluency and coherence. The base CodeReviewer—pre-trained specifically for code review on a multilingual corpus—achieves lower BLEU but competitive human-rated scores, highlighting a trade-off between lexical similarity and perceived quality.

CodeLlama-7B, fine-tuned on the same monolingual setting, shows balanced performance. While its BLEU-4 score is slightly lower than CodeReviewer's, it achieves the highest Information and strong Relevance scores, demonstrating that instruction-tuned, code-pretrained LLMs can generate informative and context-aware comments after fine-tuning. Its base model, trained on multilingual data, performs considerably worse across all metrics, underscoring the importance of task adaptation.

DeepSeek-R1-Distill-Llama-8B presents a different trade-off. Fine-tuning on monolingual data significantly boosts BLEU, but slightly reduces Information and Relevance compared to its base model. Notably, the base model achieves the highest Relevance score overall, despite its low BLEU, suggesting that fine-tuning may improve lexical fidelity at the expense of general reasoning and feedback richness.

4.3 Results of Code Refinement

Figure 5 shows the results of the code refinement task, comparing the performance of CodeReviewer when fine-tuned on a monolingual C# dataset versus its original multilingual version from the CodeReviewer benchmark [26]. Unlike the other tasks, fine-tuning on monolingual data led to a decline in both BLEU and EM scores. This suggests that domain and language specific fine-tuning, while effective for tasks closely tied to phrasing or review context, may be less suitable for tasks requiring a broader generalization or exposure to diverse examples. One likely reason is the significantly smaller and less varied size of the monolingual fine-tuning dataset, which may have limited the model's ability to learn complex correction patterns compared to the multilingual training corpus provided by Li et al. [26].

Model **BLEU-4** PL Scope **NL** of Comments Information Relevance CodeReviewer fine-tuned on C# (English+German) Mono-PL English+German 8.76 1.20 1.41 CodeReviewer fine-tuned on C# (English) Mono-PL **English-only** 9.08 3.47 3.16 CodeLlama-7B fine-tuned on C# Mono-PL **English-only** 8.08 3.80 3.67 DeepSeek-R1-Distill-Llama-8B fine-tuned on C# Mono-PL **English-only** 8.12 3.48 3.61 CodeReviewer base [26] Multi-PL Multilingual 5.32 3.60 3.20 CodeLlama-7B base [17] Multi-PL Multilingual 5.58 3.13 3.45 DeepSeek-R1-Distill-Llama-8B base [15] Multi-PL Multilingual 3.45 3.93 3.61

Table 3: Comparison of models on the review comment generation task, categorized by PL scope and NL of comments.

The best score for each metric is shown in bold.

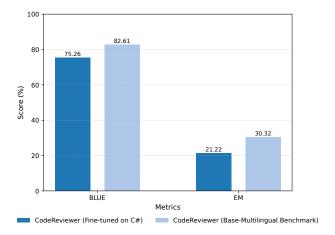


Figure 5: Code refinement performance of CodeReviewer fine-tuned on monolingual C# data compared to its base multilingual version.

4.4 Comparison of LMs, SonarQube, and Human Reviewers

Figures 6 and 7 present the comparative performance of human reviewers, SonarQube, and LMs across the two main evaluation tasks—code change quality estimation and review comment generation—based on a subset of 40 PRs from our industrial C# dataset.

Code Change Quality Estimation. For the binary classification task of identifying whether a code change requires a review comment, both SonarQube and the fine-tuned CodeReviewer performed close to human reviewers in terms of accuracy, precision, recall, and F1 score (see Figure 6). A quantitative analysis of prediction errors across issue categories revealed notable performance differences between the methods. SonarQube showed strong performance in detecting rule-based issues, such as security vulnerabilities and maintainability concerns. However, it struggled with more context-dependent categories like performance optimizations and logic errors. In contrast, the fine-tuned CodeReviewer delivered more balanced results across all issue types, suggesting better generalization capabilities for identifying both rule-based and context-sensitive quality issues.

Review Comment Generation. In the review comment generation task, the performance gap between human reviewers and automated methods became more pronounced (see Figure 7). Humans consistently produced comments with higher Information and Relevance scores across all PRs. Among the LMs, CodeLlama-7B (fine-tuned on C#) achieved the best human evaluation scores, outperforming both SonarQube and the other LMs. Notably, the DeepSeek-RI-Distill-Llama-8B model produced almost identical comments before and after fine-tuning. This suggests that fine-tuning reduced its instruction-following and reasoning capabilities. While its BLEU score increased post-fine-tuning, this improvement came at the cost of reduced explanatory richness and contextual reasoning.

Efficiency Trade-offs. Table 4 presents the average review time per PR for each method. Human reviewers typically required over five minutes per PR, depending on the complexity of the changes. SonarQube took between three to five minutes due to its thorough static analysis. In contrast, LMs significantly reduced review time, generally completing reviews in under one minute. Among them, the DeepSeek-R1-Distill-Llama-8B base was the slowest, likely due to its more elaborate reasoning-based responses.

Table 4: Average time-to-review per PR by method. Measurements reflect end-to-end processing time across the full evaluation dataset, not limited to the 40 PRs used for human comparison.

Method	Time-to-Review (min)	
DeepSeek-R1-Distill-Llama-8B base	1-3	
Other LMs	<1	
SonarQube	3-5	
Human Reviewers	5-7	

5 DISCUSSION

5.1 Effectiveness of Monolingual Fine-Tuning for CodeReviewer on Code Change Estimation and Refinement Tasks

Our findings provide empirical evidence that monolingual finetuning on C# can enhance the performance of CodeReviewer, particularly in the Code Change Quality Estimation task. Despite being trained on a smaller dataset, the monolingual fine-tuned variant

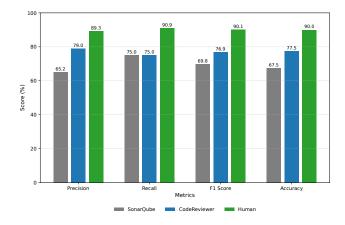


Figure 6: Code change quality estimation performance of SonarQube, CodeReviewer and human reviewers on 40 PRs. The CodeReviewer was fine-tuned on C# with English comments.

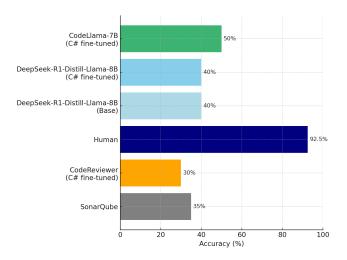


Figure 7: Review comment generation performance of Sonar-Qube, CodeReviewer and human reviewers on 40 PRs. The CodeReviewer was fine-tuned on C# with English comments.

consistently outperformed its multilingual counterpart. This supports previous research indicating that language-specific adaptation helps models better capture syntactic patterns and task-specific signals [1, 7].

An important methodological factor contributing to this outcome was our negative sample selection strategy. We deliberately included only the final code hunk of each PR as negative examples (i.e., those not requiring a review comment). These hunks typically contained fewer and more stable changes, making the learning task less noisy. This targeted sampling likely helped the model to more effectively learn decision boundaries between review-worthy and non-review-worthy code changes, echoing findings from prior work on label quality and class balance in code classification tasks [18].

However, these benefits did not extend to the Code Refinement task. The monolingual fine-tuned model underperformed the multilingual baseline in both BLEU and exact match scores. One plausible reason is the limited size and diversity of the monolingual training data, which may have constrained the model's ability to generalize to broader or more complex edit patterns. Prior work has emphasized that code generation tasks, such as refinement, benefit from large and diverse datasets [26, 27]. Additionally, translation-related inconsistencies in the dataset may have introduced noise, a known threat to generation quality in multilingual settings [62].

These observations highlight a task-dependent trade-off: Monolingual fine-tuning improves classification and structured decision tasks but may hinder performance on semantically rich, generation-oriented tasks.

5.2 Influence of Model Type, PL/NL Scope, and Fine-Tuning Design on Review Comment Generation

Our results highlight that while monolingual fine-tuning on C# improves LM performance in Review Comment Generation, the relationship between BLEU-4 scores and human-perceived comment quality is not straightforward. Although the fine-tuned CodeReviewer achieved the highest BLEU-4 score, human evaluators consistently rated the fine-tuned CodeLlama-7B higher in both Information and Relevance. This discrepancy underscores known limitations of BLEU-4 as a sole quality indicator for code-related NL generation tasks [26, 62].

One likely reason for CodeReviewer's high BLEU-4 score lies in its learned use of token patterns such as emojis, which appeared frequently in the training data. Although such token patterns increased lexical similarity and improved BLEU-4 scores, they did not necessarily contribute to the informativeness or contextual relevance of the generated comments. Moreover, the mixed-language composition (English and German) of the fine-tuning data for some CodeReviewer variants likely introduced linguistic inconsistencies, occasionally resulting in comments that were difficult to understand or exhibited unnatural language mixing. This finding aligns with studies showing that inconsistencies in training data language composition can negatively affect LMs generation quality [8].

A noteworthy observation emerged with DeepSeek-R1-Distill-Llama-8B. Before fine-tuning, this reasoning-focused LLM produced comments that human evaluators perceived as more context-aware and insightful. However, after fine-tuning on our instruction-light dataset, the model's BLEU-4 score improved, but its ability to generate reasoning-rich, explanatory comments declined. This suggests that for models like DeepSeek-R1, maintaining reasoning capabilities may require specialized fine-tuning approaches that preserve or enhance CoT reasoning during adaptation.

Overall, these findings demonstrate that while monolingual finetuning helps align LMs with the target PL and improves surfacelevel lexical similarity, it may introduce trade-offs in reasoning quality and linguistic richness. These trade-offs are further shaped by the underlying pretraining paradigms of the LMs. Their divergent behaviors after fine-tuning illustrate how pretraining objectives influence adaptability to domain-specific tasks like code review. We recommend integrating more linguistically balanced and instruction-rich datasets—possibly including human-annotated reasoning traces—to better support both fluency and depth in generated review comments.

5.3 Comparison of Fine-Tuned LMs, SonarQube, and Human Reviewers

Our findings reveal that while monolingual fine-tuning improves LLM performance across code review tasks, human reviewers still consistently outperform both LLM-based models and ASATs like SonarQube. This performance gap was especially pronounced in the Review Comment Generation task, where human comments were rated higher in both Information and Relevance. These results align with prior studies showing that human reviewers provide more actionable, context-aware, and nuanced feedback than current automated tools [8, 18].

In the Code Change Quality Estimation task, the fine-tuned CodeReviewer showed a noticeable drop in performance when evaluated on our diverse, industrial PR sample compared to its controlled test set results. This degradation likely reflects the domain shift and code diversity in real-world PRs—an issue commonly noted in prior LLM-based software engineering studies [26, 29]. Unlike more homogeneous training and testing datasets, our industrial PRs represented varied coding styles, standards, and project-specific conventions, reinforcing concerns raised by Vassallo et al. [59] regarding tool generalizability.

SonarQube, as expected from prior ASAT studies [4, 6], performed well in identifying rule-based issues like code smells and security vulnerabilities. However, its lack of semantic understanding limited its ability to detect deeper logic-related or architectural flaws—consistent with earlier critiques of ASATs[38].

The LLM-based models, particularly the fine-tuned CodeLlama-7B, demonstrated better generalization across issue categories, especially for refactoring suggestions and clarity improvements. This aligns with recent findings that LLMs can capture higher-level code semantics more effectively than rule-based tools [31]. However, even the best-performing LLM still lagged behind human reviewers in delivering comprehensive, context-sensitive feedback—a limitation similarly reported in [8].

An important observation was the trade-off between review speed and review quality. While both LMs and SonarQube completed reviews significantly faster than humans (often under one minute), their feedback lacked the depth and accuracy required for critical code assessment. This reflects a broader trend in AI-assisted code review research, where efficiency gains often come at the expense of review depth and trustworthiness [62].

Overall, while AI and SonarQube offer substantial efficiency gains, they still fall short of human reviewers in producing high-quality, context-aware feedback. These results suggest that AI tools can serve as valuable assistants to accelerate the review process but cannot yet fully replace expert human judgment in critical code assessment tasks. A hybrid approach—combining the speed of AI with human expertise—may represent the most effective strategy for industrial code review workflows.

6 IMPLICATIONS

Our findings offer practical implications for both industry practitioners and researchers.

For practitioners, fine-tuned LMs can serve as fast and reasonably accurate assistants in CI pipelines. While they do not match human-level performance—particularly in nuanced or complex review scenarios—their speed and early-issue detection capabilities make them valuable for triage and prioritization tasks. In particular, LMs can help filter routine PRs, reducing the cognitive load on human reviewers.

Integrating LM-based tools with static analyzers like SonarQube can lead to more balanced workflows. Whereas SonarQube is effective in flagging rule-based issues (e.g., security or maintainability violations), LMs offer more linguistically rich and context-sensitive feedback. This division of labor enables efficient issue coverage across both syntactic and semantic dimensions.

Another benefit is cost-efficiency. The evaluated tools—CodeReviewer, CodeLlama-7B, and DeepSeek-R1—are open-source and license-free, providing accessible solutions for organizations operating under budget constraints. Moreover, task-specific monolingual fine-tuning emerged as a practical strategy to improve model effectiveness in single-language environments like C#.

For researchers, our results raise concerns about relying solely on automated metrics such as BLEU to assess code review quality. Human-centered evaluations remain crucial for capturing relevance and informativeness. In addition, the performance drop observed in reasoning-intensive models like DeepSeek-R1-Distill after fine-tuning suggests a need for strategies that preserve reasoning capabilities—potentially via chain-of-thought data or multi-objective optimization approaches.

7 THREATS TO VALIDITY

Our study has several validity threats, discussed in terms of internal, external, and construct validity.

Internal Validity. One threat is the limited size and language scope of the monolingual C# dataset. The small volume of high-quality code-review pairs may have restricted the models' exposure to diverse code patterns, especially in the Code Refinement task. Additionally, translating German review comments into English may have introduced semantic noise, affecting both model learning and human evaluation.

Evaluation variability presents another threat. Although six professional software engineers with varying experience levels rated the outputs, subjective bias remains possible. We mitigated this by averaging scores and resolving annotation disagreements through consensus-based discussion.

External Validity. Our experiments focused on C# from a single industrial partner, supplemented with open-source data. This limits generalizability to other languages or organizational contexts. Replications on other languages and datasets are needed to confirm broader applicability.

Construct Validity. Relying on BLEU for comment evaluation is a known threat, as BLEU captures lexical similarity but may miss semantic quality. To mitigate this, we complemented BLEU with human-centered Information and Relevance ratings. Still, evaluating LLM-generated review quality remains challenging. The choice

of baselines may influence results. We used strong open-source models (CodeReviewer, CodeLlama-7B, DeepSeek-R1-Distill-Llama-8B), but comparisons with proprietary models like GPT-40 were beyond our computational resources and budget limitations. Also, for practical reasons, we did not perform multi-run evaluations for each setting, meaning variance across runs remains possible for non-deterministic models like DeepSeek-R1-Distill-Llama-8B.

8 CONCLUSION AND FUTURE WORK

This study examined whether fine-tuning different types of LMs, including a PLM specialized in code review (CodeReviewer), a LLM pretrained on code (CodeLlama-7B), and a general-purpose LLM (DeepSeek-R1-Distill), on monolingual C# data that combines public benchmarks with proprietary industrial code yields performance gains over their original multilingual versions. We evaluated these models across three core code review tasks and compared their performance against both an ASAT and human reviewers.

The overall findings show that human reviewers still deliver the highest quality and most context aware feedback. They are able to capture nuances and understand the deeper implications of code changes in ways that current LMs and ASATs cannot. Nevertheless, the AI-based approaches and SonarQube offer valuable benefits, such as significantly faster review times and consistent output. For instance, the AI models performed well in quickly identifying whether a PR needed a review, even if their generated comments were not always as detailed or accurate as those provided by human experts. These findings highlight the potential of integrating AI-driven code review tools into existing workflows. By combining the speed and efficiency of automated systems with the deep, contextual understanding of human reviewers, it is possible to create a more balanced and effective approach to maintaining high software quality. More detailed information on our experimental setups, parameter settings, and evaluation procedures can be found in our repository.

Future research may expand to other object-oriented languages to assess cross-language generalizability. Incorporating structural representations like Abstract Syntax Trees could enhance model understanding. Additionally, applying CoT fine-tuning may improve the reasoning transparency of LLM-generated feedback.

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