

Evaluation and Benchmarking of Large Language Models for Code Generation Tasks

1. Introduction

Large Language Models (LLMs) have demonstrated strong capabilities in program synthesis and code generation. However, evaluating their performance remains a challenging problem. Traditional evaluation approaches rely on **execution-based correctness**, while recent research has explored **LLM-as-a-Judge** paradigms, where a strong language model evaluates generated code based on semantic understanding.

In this project, we perform a **systematic evaluation and benchmarking of multiple open-source LLMs** on Python code generation tasks using two complementary approaches:

1. **Execution-based evaluation** using the HumanEval and HumanEvalNext benchmarks.
2. **LLM-as-a-Judge evaluation**, where a powerful code-focused LLM (Qwen2.5-Coder-7B-Instruct) scores generated solutions.

The goal is to analyze:

- Code correctness (pass@k),
- Diversity of generated solutions,
- Textual similarity (BLEU),
- And alignment between execution-based and judge-based evaluation.

2. Datasets

2.1 HumanEval

HumanEval is a widely-used benchmark for evaluating code generation models. It consists of 164 Python programming problems, each with:

- A function signature and docstring prompt
- Hidden unit tests used for execution-based validation

2.2 HumanEvalNext

HumanEvalNext is a more challenging extension of HumanEval that introduces:

- More complex test cases
- Higher sensitivity to edge cases

3. Models Evaluated

The following models ($\approx 7B$ parameters) were evaluated:

- **Code-specialized models**

- CodeLlama-7B-Python
- CodeLlama-7B-Instruct
- DeepSeek-Coder-6.7B-Instruct
- Qwen2.5-Coder-7B-Instruct
- StarCoder2-7B
- Magicoder-S-DS-6.7B
- aiXcoder-7B

- **General-purpose models**

- Mistral-7B

This selection enables comparison between **instruction-tuned**, **code-specialized**, and **general LLMs**.

4. Evaluation Methodology

4.1 Execution-Based Evaluation

Execution-based evaluation was performed using the **Hugging Face code_eval metric**, which executes generated code against hidden unit tests.

Metrics:

- **pass@5**: Probability that at least one of five generated solutions is correct
- **BLEU score**: Measures textual similarity with reference solutions
- **Unique Solution Rate**: Measures diversity among generated samples

Each problem was sampled **5 times** using stochastic decoding (temperature = 0.7).

4.2 LLM-as-a-Judge Evaluation

In the second phase, generated solutions were evaluated using **Qwen2.5-Coder-7B-Instruct as a judge model**.

Scoring Rubric:

- **1.0** – Correct solution for all cases
- **0.5** – Minor bug or missing edge case

- **0.0** – Incorrect, incomplete, or invalid code

For each problem:

- 5 candidate solutions were generated
- The judge model provided:
 - Individual scores
 - Natural language explanations
- Aggregated metrics were computed for all the average scores of the five candidate solutions of each problem:
 - Mean score
 - Max score
 - Diversity score

This approach allows evaluation **without executing code**, simulating human-like reasoning.

5. Execution-Based Evaluation Results

5.1 Pass@k Performance

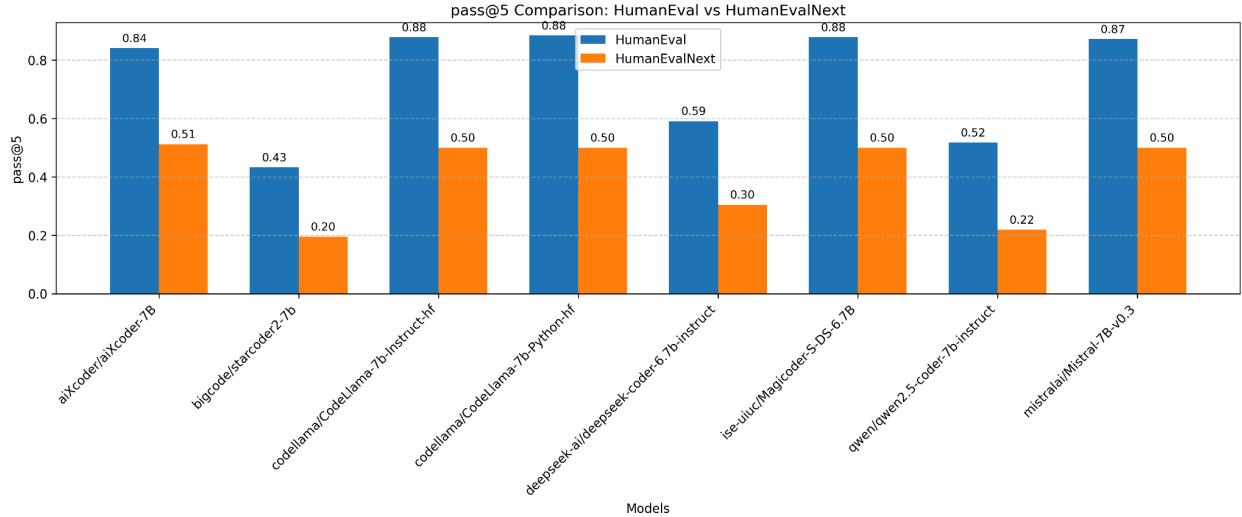


Figure 1: Pass@5 Results

Observation:

- CodeLlama and Magicoder achieve the highest execution correctness.
- Performance drops significantly on **HumanEvalNext**, indicating sensitivity to harder test cases.

5.2 Diversity and BLEU

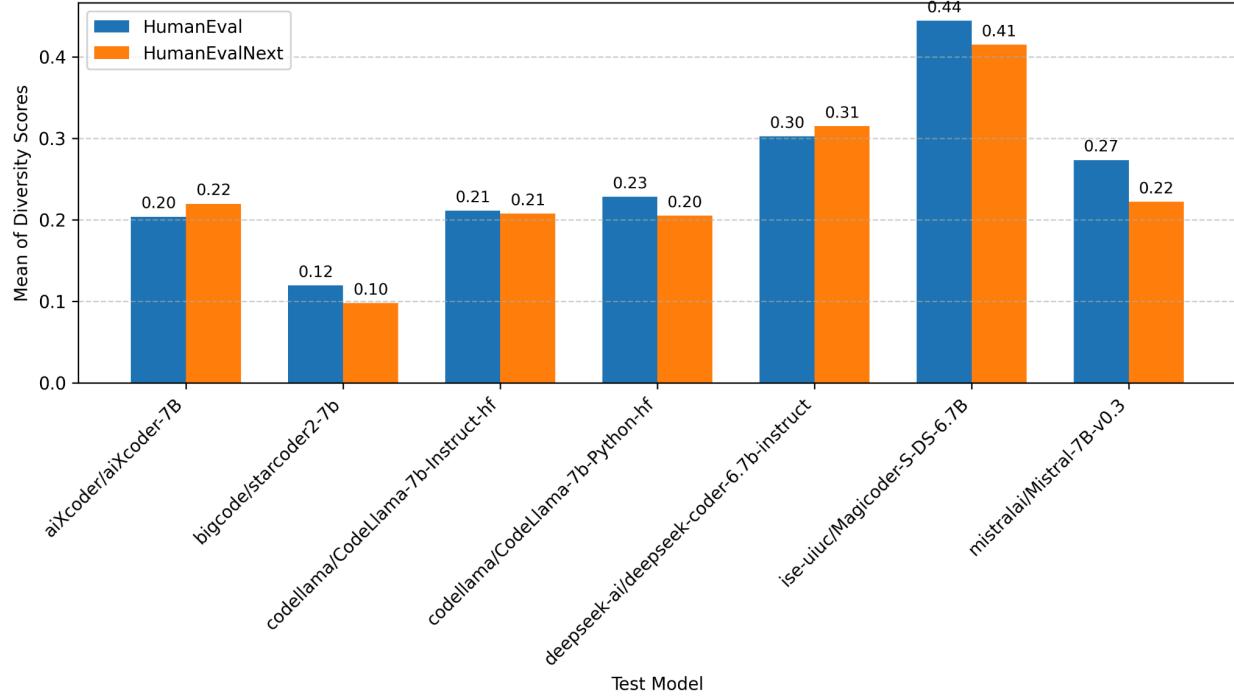


Figure 2: Diversity Results

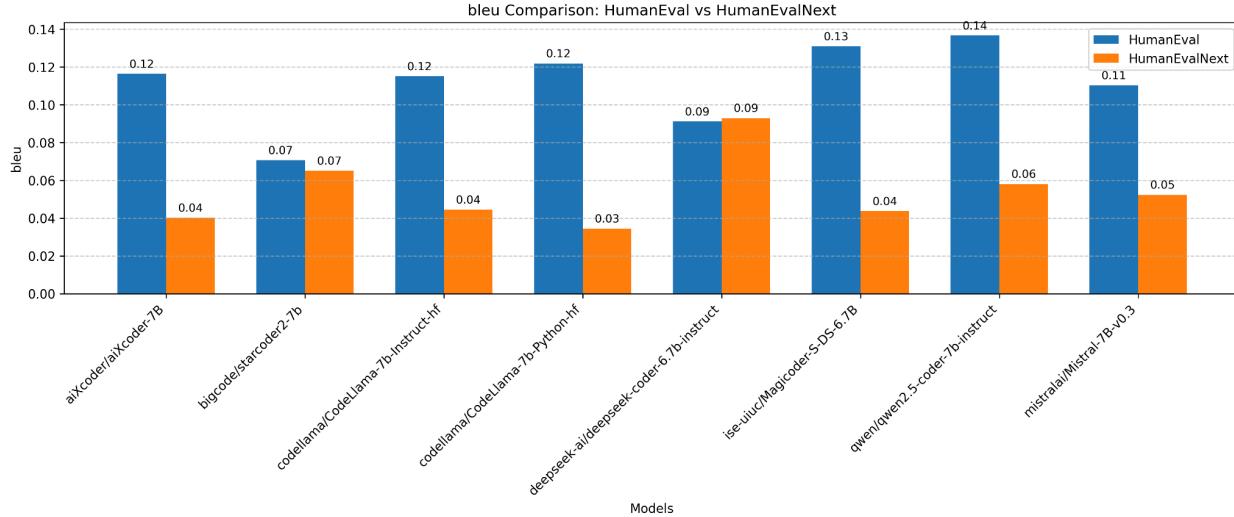


Figure 3: Blue comparison

- **BLEU scores are consistently low**, confirming that:
 - Correct solutions may be structurally different
 - BLEU is poorly correlated with functional correctness

6. LLM-as-a-Judge Results

6.1 Mean Judge Scores

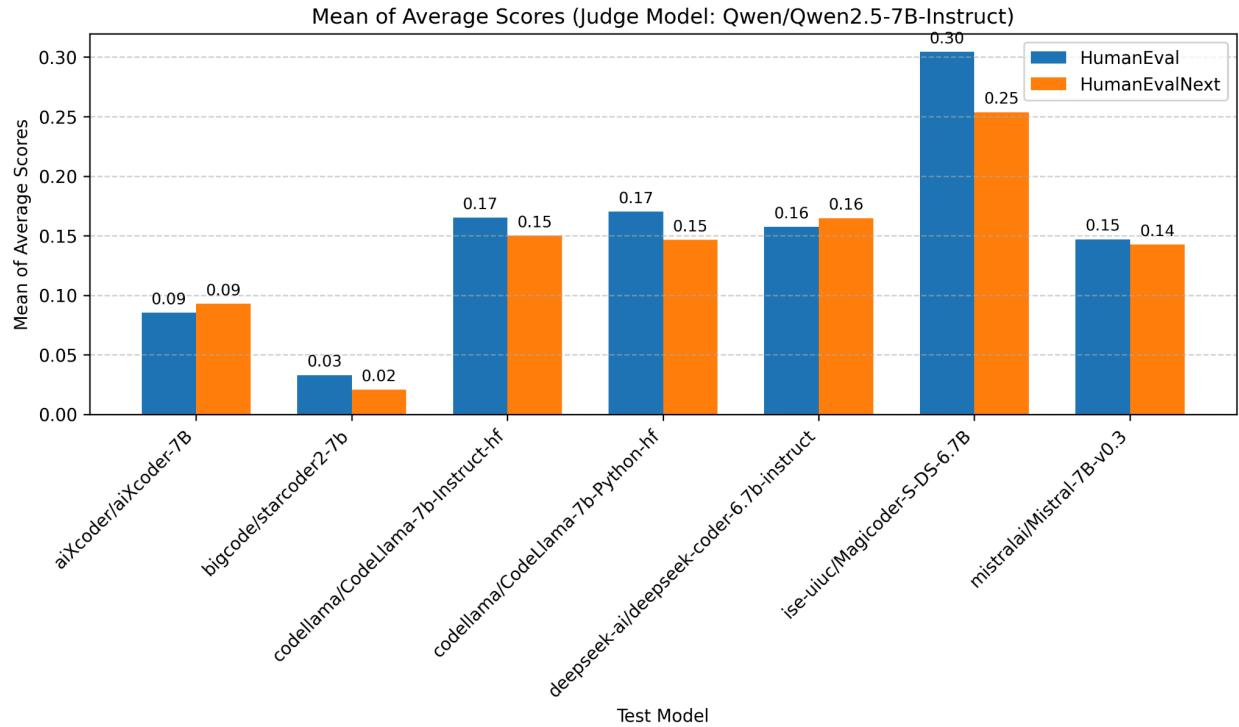


Figure 4: Mean Average Scores

Observation:

Judge scores are **much lower in absolute value** compared to pass@k, indicating:

- Stricter semantic evaluation
- Penalization of partial correctness and edge case failures

6.3 Percentage of Maximum Scores

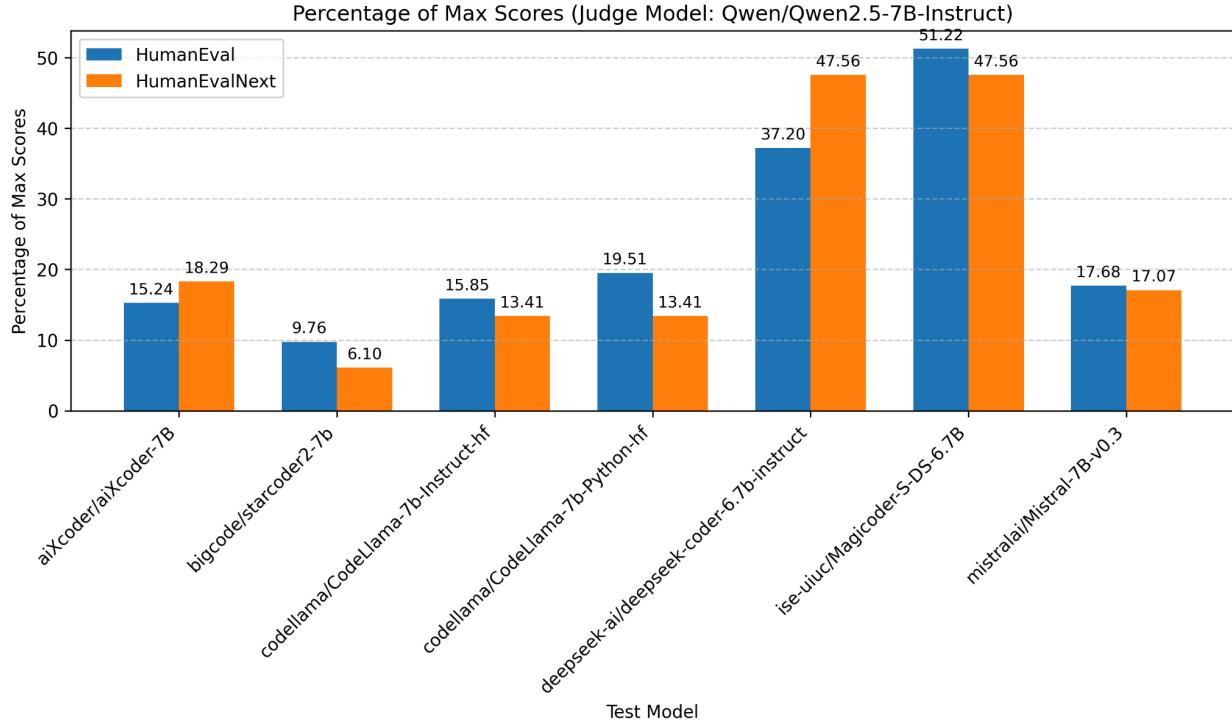


Figure 5: Percentage of max scores

7. Limitations

Despite its contributions, this study has several limitations. First, the LLM-as-a-judge framework relies on a single judge model, which may introduce bias toward the judge’s own training distribution or coding style preferences. Second, judge-based scoring is computationally expensive, as it requires running an additional large model for every generated candidate. Third, although care was taken to standardize prompts and scoring rubrics, natural language explanations generated by the judge model may occasionally be inconsistent or hallucinated. Finally, judge-based scores are not directly comparable to pass@k metrics, which limits their interpretability as absolute performance measures.

8. Future Work

Future work could extend this study in several directions. One promising direction is the use of multiple judge models or ensemble-based judging to reduce single-model bias and improve robustness. Another avenue is calibrating judge scores against execution-based metrics to better align semantic judgments with functional correctness. Additionally, scaling the evaluation to larger benchmarks and more recent models could provide deeper insights into emerging trends in code generation. Finally, incorporating human evaluation or hybrid human–LLM judging could further improve reliability and provide richer qualitative feedback on generated code.

9. Conclusion

This project presented a comprehensive evaluation and benchmarking study of multiple open-source large language models for Python code generation. Two complementary evaluation paradigms were explored: execution-based evaluation using established benchmarks (HumanEval and HumanEvalNext) and an LLM-as-a-judge framework leveraging a strong code-oriented model. The execution-based results demonstrated that code-specialized and instruction-tuned models such as Magicoder, CodeLlama, and DeepSeek-Coder consistently achieved higher functional correctness, particularly on the original HumanEval benchmark. Performance degradation across all models on HumanEvalNext highlighted the increased difficulty of the benchmark and underscored limitations in generalization and edge-case handling.

The LLM-as-a-judge evaluation provided additional insights beyond binary correctness. Judge-based scores were generally lower in magnitude, reflecting stricter semantic scrutiny and sensitivity to partial correctness, logical flaws, and missing corner cases. Importantly, the relative ranking of models under judge-based evaluation largely aligned with execution-based results, suggesting that LLM judges can serve as a meaningful proxy for correctness when unit tests are unavailable. Furthermore, diversity analysis revealed that stronger models not only produced more correct solutions but also generated a broader range of distinct solution strategies, indicating deeper problem understanding.

Overall, this work demonstrates that execution-based and judge-based evaluations capture complementary aspects of code generation quality. While execution-based metrics remain the gold standard for correctness, LLM-as-a-judge methods offer interpretability, flexibility, and applicability in scenarios where automated testing is infeasible.

References

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