**Literature Review: Enhancing Identifier Naming with Large Language Models (LLMs)**

**1. Introduction**

Code readability plays a crucial role in software maintainability and comprehension. Poorly named identifiers can make code difficult to understand and maintain, leading to increased debugging time and errors. Automated identifier renaming has emerged as a promising approach to improving code quality by leveraging **Large Language Models (LLMs)**.

The paper **"Enhancing Identifier Naming Through Multi-Mask Fine-Tuning of Language Models of Code"** by Vijayvargiya et al. (2024) explores a novel approach to identifier renaming using a fine-tuned **GraphCodeBERT** model. This literature review discusses the study’s methodologies, datasets, evaluation metrics, key findings, and research implications.

**2. Summary of the Reviewed Study**

**2.1 Research Goal**

The study aims to **enhance variable renaming** using **fine-tuned transformer-based models**. It investigates how well an identifier-aware language model can **predict meaningful variable names**, making the process of refactoring more effective.

**2.2 Methodology and Datasets**

The research utilizes **masked language modeling (MLM)** to train a **GraphCodeBERT** model specifically for identifier renaming. The key dataset includes:

* **236,745 high-quality identifiers** from **50 GitHub repositories**.
* Full Java class contexts to maintain identifier relationships.
* Filtration techniques to remove **low-quality and ambiguous identifiers**.

**2.3 Evaluation Metrics**

The model’s performance is assessed using:

* **Pseudo-perplexity (PPPL)** – Measures how confidently the model predicts masked tokens.
* **Negative Pseudo-Likelihood (PLL)** – Evaluates the likelihood of correct identifier generation.
* **Developer Survey** – Gathers insights on identifier quality and readability.

**2.4 Key Findings**

1. The fine-tuned **GraphCodeBERT** model significantly improves identifier prediction, reducing perplexity from **363 to 36**.
2. The **confidence-based inference technique** enhances identifier renaming by adjusting token lengths dynamically.
3. Human evaluations indicate that fine-tuned models generate **better identifier names** than non-specialized LLMs, performing competitively with **GPT-4 and Gemini Pro**.

**3. Reflection and Research Insights**

**3.1 Contributions**

* Proposes an **identifier-aware fine-tuning** approach to **GraphCodeBERT**.
* Introduces a **high-quality dataset** for training identifier renaming models.
* Validates the effectiveness of **confidence-based inference** for dynamic identifier length prediction.

**3.2 Limitations**

* **Limited to Java code** – Needs further testing across multiple programming languages.
* **Contextual dependency** – Struggles with naming long, descriptive variables.
* **Reliance on training data** – Performance may degrade for identifiers not seen in training.

**3.3 Future Research Directions**

* Expanding the dataset to **multi-language repositories**.
* Integrating **static code analysis techniques** for improved semantic awareness.
* Developing a **human-in-the-loop framework** to refine identifier renaming suggestions.

**4. Conclusion**

This study demonstrates that **fine-tuned LLMs can significantly enhance automated variable renaming**, making code **more readable and maintainable**. However, **cross-language adaptability** and **semantic understanding improvements** remain key areas for future research.

**References**

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