

# CoMIND: TOWARDS COMMUNITY-DRIVEN AGENTS FOR MACHINE LEARNING ENGINEERING

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## ABSTRACT

Large language model (LLM) agents show promise in automating machine learning (ML) engineering. However, existing agents typically operate in isolation on a given research problem, without engaging with the broader research community, where human researchers often gain insights and contribute by sharing knowledge. To bridge this gap, we introduce MLE-Live, a live evaluation framework designed to assess an agent’s ability to communicate with and leverage collective knowledge from a simulated Kaggle research community. Building on this framework, we propose CoMind, a multi-agent system designed to systematically leverage external knowledge. CoMind employs an iterative parallel exploration mechanism, developing multiple solutions simultaneously to balance exploratory breadth with implementation depth. On 75 past Kaggle competitions within our MLE-Live framework, CoMind achieves a 36% medal rate, establishing a new state of the art. Critically, when deployed in eight live, ongoing competitions, CoMind outperforms 92.6% of human competitors on average, placing in the top 5% on three official leaderboards and the top 1% on one.

## 1 INTRODUCTION

The capabilities of large language model (LLM)-based agents are rapidly advancing, showing significant promise in automating complex tasks across domains including software engineering (Jimenez et al., 2024; Merrill et al., 2026), mathematical problem-solving (Ren et al., 2025; Wu et al., 2025; Collins et al., 2025; Li et al., 2026), and scientific discovery (Romera-Paredes et al., 2024; Yamada et al., 2025; Sun et al., 2025; Feng et al., 2026). A particularly challenging and impactful frontier for these agents is machine learning engineering (MLE). Automating the multifaceted MLE pipeline, which spans the design, implementation, and rigorous evaluation of high-performance models, remains a critical test of an agent’s autonomous reasoning and decision-making abilities.

Recent advances have introduced LLM agents capable of autonomously developing machine learning pipelines for Kaggle-style competitions (Chan et al., 2025). Current approaches have demonstrated a range of techniques, from the ReAct-style reasoning in MLAB (Huang et al., 2024) and the tree-based exploration of AIDE (Jiang et al., 2025), to the skill-specialized multi-agent system of AutoKaggle (Li et al., 2024). Although these systems represent important steps toward automating MLE, they are fundamentally designed to operate in isolation, exploring the solution space individually.

This isolated approach stands in stark contrast to how human experts operate. In real-world data science competitions and research, participants thrive on community knowledge sharing: learning from public discussions, shared code, and collective insights to enhance solution quality and drive innovation (Wuchty et al., 2007). By failing to engage with this dynamic external context, current agents are prone to converging on repetitive strategies and ultimately plateauing in performance. This critical gap motivates our central research question:

*How can we **evaluate** and **design** research agents that utilize collective knowledge?*

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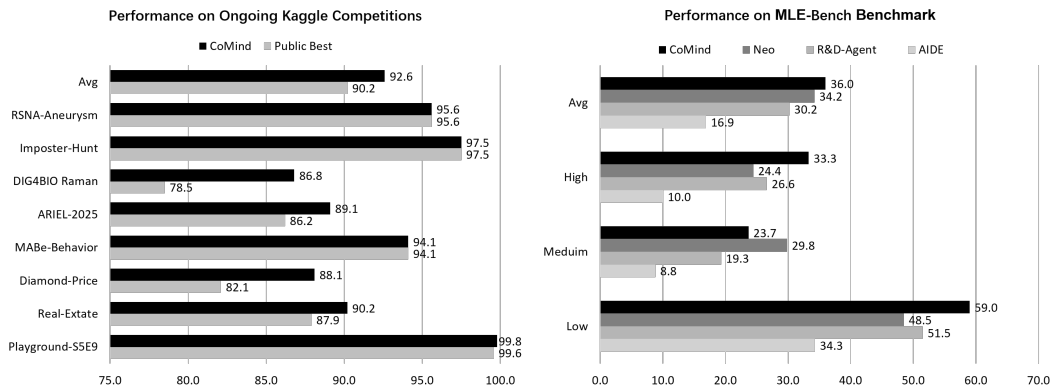


Figure 1: **Left:** CoMind’s win rates on eight ongoing Kaggle competitions compared with the public best entry. **Right:** Any Medal results on 75 MLE-Bench competitions grouped by task difficulty levels. CoMind achieves state-of-the-art performance on MLE-Bench compared to strong baselines.

To address this question, we introduce **MLE-Live**, a controllable evaluation framework that simulates realistic Kaggle-style research communities with time-stamped public discussions and shared code artifacts that public before competition deadline. This ensure the information access is same as human participant. MLE-Live enables rigorous evaluation of agents’ ability to leverage community knowledge in temporally grounded settings, supporting both offline evaluation on past competitions and online evaluation on ongoing competitions.

Building upon this framework, we propose **CoMind**, a multi-agent system designed to systematically incorporate external knowledge and iteratively refine solutions. CoMind’s architecture consists of five specialized agent role operating in concert. A central *Coordinator* manages the overall workflow and community interactions. To process external knowledge, an *Analyzer* first summarizes and suggests on improvements and weaknesses for a curated group of solutions, while an *Idea Proposer* brainstorms a diverse pool of ideas and synthesizes novel strategies. These strategies are then passed to multiple parallel *Coding Agents* for implementation and report generation. Finally, a dedicated *Evaluator*, which creates robust scripts for solution assessment and selection. This collaborative process allows CoMind to effectively utilize external community knowledge and construct novel solution for the targeted research problem.

We conducted a comprehensive, two-pronged evaluation to assess CoMind’s performance in both static and live environments. First, on a static benchmark comprising 75 past Kaggle competitions from MLE-Bench (Chan et al., 2025), CoMind achieved an overall medal rate of 0.36, establishing a new state of the art by significantly outperforming prior leading agents such as Neo and ML-Master (Liu et al., 2025). Second, to validate its real-world practicality, we deployed CoMind in eight ongoing Kaggle competitions (detailed in Figure 1). In this challenging live setting, CoMind proved highly effective, achieving an average rank better than 92.6% of human competitors while placing in the top 5% on three official leaderboards and the top 1% on one. These results demonstrate CoMind’s robust effectiveness against contemporary challengers.

In summary, our contributions are:

- **MLE-Live:** A live evaluation framework simulating community-driven machine learning research with realistic shared discussions and code.
- **CoMind:** A novel agent excelling at collective knowledge utilization and iterative exploration, achieving medal-level performance in real competitions.
- **Community-Driven Multiagent Collaboration:** An iterative parallel exploration mechanism enabling continuous knowledge accumulation.

## 2 RELATED WORK

The rise of large language models (LLMs) has sparked a new wave of research into LLM-driven agents, systems that leverage LLMs’ reasoning and language capabilities to autonomously perceive,

plan, and act within digital or physical environments. Early works such as ReAct (Yao et al., 2023; Schick et al., 2023; Shen et al., 2023; Hong et al., 2023; Boiko et al., 2023) introduced frameworks that transform LLMs into programmable reasoning engines by interleaving natural language reasoning with tool-use actions. Subsequent studies have extended these agents to various domains, including computer usage (Xie et al., 2024; Zhou et al., 2024) and software development (Wang et al., 2025; Jimenez et al., 2024).

In parallel, the field of automated machine learning (AutoML) aims to reduce human involvement in building ML pipelines by automating tasks such as model selection, hyperparameter tuning, and architecture search. Early systems like Auto-WEKA (Thornton et al., 2013), HyperBand (Li et al., 2018) and Auto-sklearn (Feurer et al., 2022) used early stopping and Bayesian optimization to search over pipeline configurations, while methods like DARTS (Liu et al., 2019) expanded automation to neural architectures. More recent frameworks such as AutoGluon (Erickson et al., 2020) and FLAML (Wang et al., 2021) emphasize efficiency and ease of use.

Building on these developments, recent efforts have applied LLM-based agents to machine learning engineering (MLE) tasks (Hollmann et al., 2023; Guo et al., 2024; Li et al., 2024; Grosnit et al., 2024; Hong et al., 2024; Chi et al., 2024; Trirat et al., 2024; Huang et al., 2024). However, most evaluations remain constrained to closed-world settings with predefined search spaces, offering limited insight into how these agents perform in open-ended or collaborative ML environments. While some agents (Guo et al., 2024; AI-Researcher, 2025) incorporate basic retrieval tools, these are typically based on simple semantic matching, and robust evaluation methodologies remain underdeveloped.

Meanwhile, several benchmarks have been proposed to evaluate machine learning (ML) engineering capabilities. MLPerf (Mattson et al., 2020) assesses system-level performance, including training speed and energy efficiency. To evaluate end-to-end ML workflows, MLAB (Huang et al., 2024) tests the capabilities of LLM-based agents across 13 ML tasks. MLE-Bench (Chan et al., 2025) and DS Bench (Jing et al., 2025) further extends to about 75 Kaggle competitions covering tasks such as preprocessing, modeling, and evaluation. However, these benchmarks typically evaluate agents in isolation, overlooking the collaborative dynamics of real-world ML development. In contrast, our work introduces a framework that simulates community-driven settings, enabling evaluation of agents’ ability to engage with and benefit from shared knowledge, while ensuring that resource access remains fair and realistic.

### 3 MLE-LIVE

Existing machine learning benchmarks typically evaluate agents in static, isolated environments. This approach fails to capture the dynamic and collaborative nature of real-world platforms like Kaggle, where progress is driven by community knowledge sharing. Participants constantly learn from shared code, public discussions, and the iterative work of others, making these community interactions a decisive factor in developing top-tier solutions.

To bridge this gap, we introduce **MLE-Live**, a live evaluation framework that extends the widely-used MLE-Bench (Chan et al., 2025). The core innovation of MLE-Live is its simulation of community interactions, providing agents with a time-stamped stream of discussions and code artifacts that mirrors the natural flow of public knowledge during a competition.

Each competition environment in MLE-Live includes the following components: (i) Task description: The background, specifications, evaluation metrics, and data structure, scraped directly from the original Kaggle competition. (ii) Competition dataset: A cleaned train-test split of the official data. When necessary, this includes reconstructed test sets to account for data that is no longer public. (iii) Submission grader: An evaluation script that precisely mimics Kaggle’s official scoring mechanism. (iv) Leaderboard: A snapshot of the final public leaderboard. (v) Community artifacts: A curated set of discussions and code notebooks that were **published before the competition deadline**. These artifacts are enriched with valuable metadata (e.g., vote counts, public scores, author tiers) to signal quality and are accompanied by any public datasets or models they reference, creating a self-contained and realistic research environment.

MLE-Live aggregates a substantial dataset of 12,951 discussions and 15,733 kernels from 75 Kaggle competitions. To ensure fairness and eliminate post-hoc data leakage, it strictly includes only resources available prior to competition deadlines, forcing agents to operate under the same information constraints as human participants. This approach offers numerous benefits for robust evaluation:

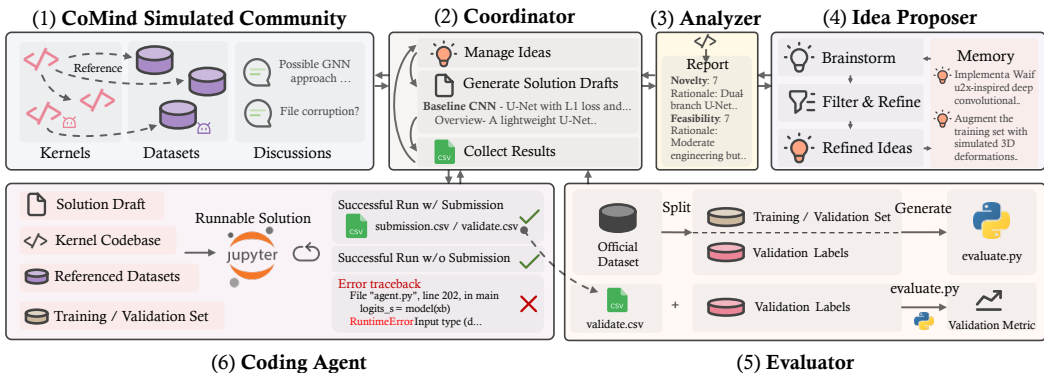


Figure 2: Overview of CoMind. Specialized agents (Coordinator, Analyzer, Idea Proposer, Coding Agent, Evaluator) interact with a simulated Kaggle community of kernels, datasets, and discussions.

it grounds agents in diverse, objectively-graded ML problems from Kaggle, while the controlled information scope allows for a fair assessment of their retrieval and reasoning abilities. These features enhance reproducibility and enable consistent, longitudinal comparisons between different agents.

## 4 COMIND

We propose **CoMind**, a community-augmented large language model (LLM) agent designed to automate machine learning (ML) engineering in an iterative, collaborative setting. Figure 2 is an overview of CoMind workflows.

### 4.1 COMMUNITY SIMULATION

CoMind’s effectiveness stems from simulating the collaborative dynamics that drive breakthrough performance in competitive ML environments. Unlike isolated automated ML systems, CoMind replicates how Kaggle participants leverage community knowledge: drawing insights from discussions, adapting public notebooks and datasets, and contributing discoveries back to the collective knowledge pool.

The simulated community is represented as  $(\mathcal{K}_t, \mathcal{D}_t, \mathcal{T}_t)$  at iteration  $t$ , where  $\mathcal{K}_t$  contains all kernels with evaluation metrics,  $\mathcal{D}_t$  includes published datasets and model checkpoints, and  $\mathcal{T}_t$  captures the dependency relationships between resources. CoMind initializes a high-quality community  $(\mathcal{K}_0, \mathcal{D}_0, \mathcal{T}_0)$  by fetching  $k_{\text{kernel}}$  top-performing kernels and  $k_{\text{discussion}}$  most popular discussions from Kaggle, along with all referenced datasets and models. The system constructs a dependency graph  $\mathcal{T}_0 = (V, E)$  where vertices represent kernels or datasets and edges capture resource dependencies.

This dependency structure enables CoMind to systematically trace solution construction, identify influential artifacts, and prioritize resources that drive performance improvements. The graph facilitates intelligent ensemble strategies by combining complementary approaches while avoiding redundant components.

CoMind operates as an active community participant, iteratively analyzing promising kernels, generating novel solutions, conducting experiments, and contributing successful results back to the community. Each iteration produces new artifacts: enhanced kernels, augmented datasets, or ensemble checkpoints, that expand the community knowledge base with associated performance metrics.

Through this continuous cycle of exploration and contribution, CoMind simulates the collaborative dynamics of competitive ML development, where collective intelligence progressively advances performance frontiers at automated scale and speed.

### 4.2 MULTI-AGENT SYSTEM

CoMind orchestrates machine learning experimentation through a coordinated multi-agent system. Specialized agents collaborate in distinct roles, mirroring the division of expertise in human research

teams across ideation, implementation, and evaluation. The workflow is an iterative loop managed by the Coordinator, which delegates tasks to the other agents.

**Coordinator** The *Coordinator* serves as **CoMind**’s central orchestration hub. Its primary responsibilities are managing the workflow, interfacing with the community environment, and allocating resources. At the start of each iteration  $t$ , the *Coordinator* initiates the process by strategically sampling promising code notebooks (kernels)  $\mathcal{K}'_t$  and relevant datasets  $\mathcal{D}'_t$  from the community. This focused sampling directs the system’s attention toward high-potential areas. After receiving refined ideas from the *Idea Proposer*, the *Coordinator* translates them into concrete solution drafts  $\mathcal{S}_t$ , which are comprehensive blueprints detailing model architecture, feature engineering, and training procedures. It then instantiates multiple *Coding Agents* in parallel, assigning each a distinct draft and all referenced resources. Upon completion, the *Coordinator* aggregates the results and publishes successful solutions back to the community, advancing the environment state for the next iteration.

**Analyzer** The *Analyzer* is responsible for distilling raw community artifacts into structured, actionable intelligence. It receives the sampled kernels and discussions from the *Coordinator* and performs a deep analysis across four key dimensions: novelty, feasibility, effectiveness, and efficiency. For each artifact, it generates a 0-10 score on these metrics, accompanied by qualitative explanations of successful patterns, emerging trends, or potential pitfalls. The output is a set of structured analytical reports  $\mathcal{R}_t$ , which serve as the primary input for the *Idea Proposer*.

**Idea Proposer** The *Idea Proposer* functions as **CoMind**’s creative engine, tasked with generating novel solution concepts. It uses the analytical reports  $\mathcal{R}_t$  from the *Analyzer* and its own persistent memory of historical ideas  $\mathcal{I}_t^*$  to ensure that new concepts are both innovative and informed by past results. The ideation process follows three phases: (1) **Brainstorming**: Generating a wide array of diverse ideas, prioritizing creativity and exploration. (2) **Filtering**: Ranking these ideas based on feasibility, potential for improvement, and alignment with the analytical reports. Only the most promising subset of ideas  $\mathcal{I}_t$  is selected. (3) **Memory Integration**: Updating its knowledge base with the newly generated ideas ( $\mathcal{I}_{t+1}^* = \mathcal{I}_t^* \cup \mathcal{I}_t$ ), allowing for increasingly sophisticated strategies over time. The final output, a filtered set of high-potential ideas  $\mathcal{I}_t$ , is sent back to the *Coordinator* to be developed into full solution drafts.

**Coding Agent** The *Coding Agent* is the implementation workhorse, responsible for converting the abstract solution drafts from the *Coordinator* into executable code. Following an iterative, ReAct-style approach, it conducts trial-and-error experiments using the training and validation data provided by the *Evaluator*. To maximize efficiency, the agent maintains a persistent Jupyter Notebook session to eliminate data reloading overhead and employs a monitor LLM to track execution and terminate failed runs immediately. This iterative process of coding, debugging, and optimization continues until a viable solution is produced or a time budget is exhausted.

**Evaluator** The *Evaluator* ensures objective, standardized, and reproducible assessment across all experiments, mirroring official Kaggle protocols. It first partitions the public dataset  $D$  into a training set  $D^*$  and a validation set with inputs  $V_x$  and ground-truth labels  $V_y$ . Crucially, only  $D^*$  and  $V_x$  are accessible to the *Coding Agents*, preserving the integrity of the validation process. When a *Coding Agent* submits predictions  $V_{\hat{y}}$ , the *Evaluator* computes the performance score using the official competition metric  $\varphi(V_{\hat{y}}, V_y)$ . It maintains a global leaderboard of all experimental runs, enabling **CoMind** to reliably track progress and make informed decisions about which solutions to prioritize and publish.

## 5 BENCHMARK EVALUATION

### 5.1 SETUP

**Task Selection.** Based on MLE-Live evaluation framework, we evaluate our agent on 75 Kaggle competitions on MLE-Bench. Using the MLE-Live framework, CoMind has access to shared discussions and public kernels published on the competition websites before the competition deadline. Since the MLE-bench test set may be constructed from Kaggle’s official public training set, and publicly available datasets or model checkpoints may have been trained on this portion of the data,

Table 1: Any Medal (%) scores on 75 MLE-Bench competitions. CoMind achieves state-of-the-art results across difficulty levels. Best results in each column are bolded. Baseline numbers are taken from the official MLE-Bench leaderboard.

Agent	Low (%)	Medium (%)	High (%)	All (%)
<b>CoMind o4-mini</b>	<b>59.09</b>	23.68	<b>33.33</b>	<b>36.00</b>
Neo multi-agent	48.48	<b>29.82</b>	24.44	34.22
R&D-Agent o3 + GPT-4.1	51.52	19.30	26.67	30.22
ML-Master deepseek-r1	48.50	20.20	24.40	29.30
R&D-Agent o1-preview	48.18	8.95	18.67	22.40
AIDE o1-preview	34.30	8.80	10.00	16.90
AIDE gpt-4o	19.00	3.20	5.60	8.60
AIDE claude-3-5-sonnet	19.40	2.60	2.30	7.50
OpenHands gpt-4o	11.50	2.20	1.90	5.10
AIDE llama-3.1-405b-instruct	8.30	1.20	0.00	3.10
MLAB gpt-4o	4.20	0.00	0.00	1.30

we restricted CoMind’s access to public datasets to minimize potential data contamination. It can only view code published by other contestants.

To validate CoMind under realistic conditions, we further evaluate CoMind on eight ongoing Kaggle competitions. These competitions span diverse domains, including tabular learning, text regression, image classification and video recognition. Rather than approximating the official scoring locally, we directly submit CoMind’s generated `submission.csv` files to the Kaggle platform, so that all reported ranks reflect genuine, live leaderboard positions.

**Implementation Details.** CoMind employs `o4-mini-2025-04-16` (OpenAI, 2025) as its backend LLM. We limit the hardware constraint of each run to 32 vCPUs and a single A6000 GPU. Each competition is evaluated in separate containers with a maximum of 24 hours to produce the final submission file. Every single code execution session is limited to 5 hour. Each Coder is limited to a maximum of 30 steps. The number of parallel agents is set to 4.

During code generation, agents are provided with the test set inputs (without labels) and prompted to generate a `submission.csv` file. The submission is then evaluated by a grader that compares the predicted labels with the ground truth. Following the setting of MLE-Bench, to avoid potential overfitting, test set labels and the competition leaderboard are strictly withheld from the agent’s accessible environment. Instead, each agent must rely solely on a self-constructed “runtime test set”, a held-out split from the original training data, for code evaluation and performance estimation.

**Metrics.** Following the evaluation metrics in MLE-Bench, we measure the performance of CoMind by **Any Medal**, the percentage of competitions where the agent earns a gold, silver, or bronze medal.

**Baselines.** We compare CoMind against the MLE-Bench leaderboard<sup>1</sup> including open-sourced systems like **R&D-Agent** (Yang et al., 2025), a dual-agent framework (Researcher/Developer) that explores multiple solution branches and merges promising ideas into improved pipelines; **ML-Master** (Liu et al., 2025), which integrates exploration and reasoning via a selectively scoped memory that aggregates insights from parallel trajectories; **AIDE** (Jiang et al., 2025), a purpose-built tree-search scaffold that iteratively drafts, debugs, and benchmarks code for Kaggle-style tasks; **OpenHands** (Wang et al., 2025), a general-purpose CodeAct-based scaffold that executes code and calls tools in a sandboxed environment; **MLAB** (Huang et al., 2024), referring to the ResearchAgent scaffold from MLEAgentBench, a general tool-calling/plan-act baseline; and **Neo** (<https://heyneo.so/>), a close-sourced multi-agent system for autonomous ML engineering.

<sup>1</sup><https://github.com/openai/mle-bench>

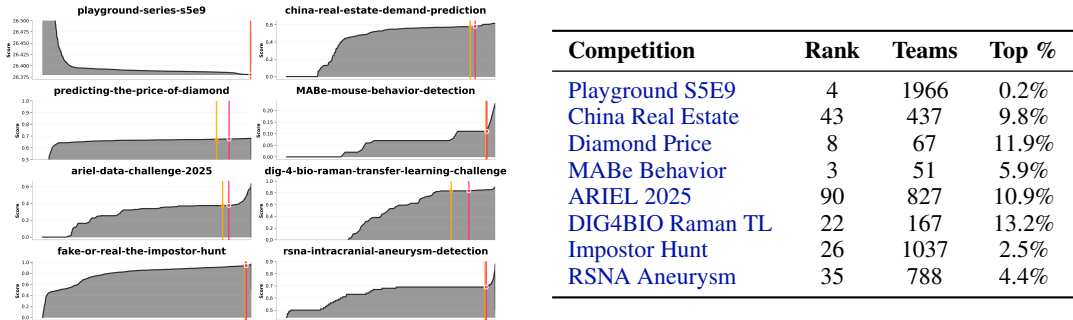


Figure 3: **Left:** Score distributions across participants in eight ongoing Kaggle competitions. Each curve shows the relationship between leaderboard rank (x-axis, inverted) and competition score (y-axis). Vertical lines indicate CoMind’s position (red) and public best performance (yellow). **Right:** Results on eight ongoing Kaggle competitions. Reported are leaderboard rank, total teams, and percentile rank (Top %, where lower means better standing).

## 5.2 RESULTS

Table 1 compares CoMind with baseline methods on 75 MLE-Bench competitions. CoMind achieves state-of-the-art performance with an *Any Medal* rate of 36.00%, significantly outperforming open-source competitors such as R&D-Agent (submitted on 2025-08-15) and surpassing the closed-source multi-agent system Neo. Appendix J provides a detailed case study on denoising-dirty-documents.

On the eight evaluated ongoing competitions, CoMind ranked top 7.35% on average and improved the best public kernel on 5 competitions. Details including authentic scores and win rates per task are provided in Figure 3. These authentic results demonstrate CoMind’s capability to tackle a variety of problem domains and achieve competitive performance in live, evolving ML workflows.

## 6 ABLATION STUDY

### 6.1 SETUP

**Task Selection.** To evaluate the impact of introducing public resources, we conducted an ablation study on 20 competitions from MLE-Bench-Lite based on MLE-Live. These tasks span across various categories, including image classification/generation, text classification/generation, image regression, audio classification, and tabular analysis.

**Baselines.** We compared CoMind against the following baselines. For consistency, all baselines use the same backend model as CoMind:

- **AIDE+Code.** To enable the use of publicly available code (e.g., Kaggle kernels), we extend AIDE with access to one public kernel per draft node, which is selected by highest community votes. AIDE+Code augments the prompt with both the task description and the selected kernel alongside the tree summarization.
- **AIDE+RAG.** We further equip AIDE with a retrieval-augmented generation (RAG) mechanism. Before generating code, the agent retrieves the titles of the top 10 voted discussions and kernels. The LLM selects the most relevant ones, receives a summarization, and then proposes its plan and implementation. For debugging or refinement, it can optionally re-query documents. Retrieval is based on cosine similarity between query and candidate document embeddings, using Multilingual E5 Text Embeddings (Wang et al., 2024).
- **CoMind w/o  $\mathcal{R}$ .**  $\mathcal{R}$  denotes all public resources. In this variant, CoMind operates without access to any external community resources. It starts with an empty community and relies solely on its own generation history to propose candidate ideas and assemble solution drafts.

**Metrics.** Following the evaluation metrics in prior research (Chan et al., 2025), the relative capability of generating high-quality solution compared with human is measured by:

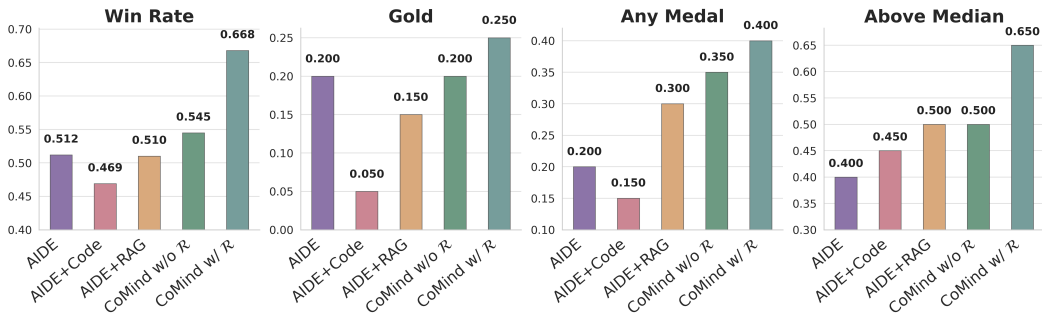


Figure 4: **Performance of CoMind and other baselines on 20 competitions from MLE-Bench-Lite.** *Valid Submission* is the ratio of submissions meeting format requirements and validation criteria. *Win Rate* is the percentage of human competitors outperformed by the agent. *Any Medal*, is the proportion of competitions where the agent earned Gold, Silver or Bronze medals. *Above Median* is the fraction of competitions where the agent’s score strictly exceeded the median human competitor.

Table 2: **Average win rate of CoMind and other baselines across task categories on 20 competitions from MLE-Bench-Lite.** *# of Tasks* refers to the number of competitions in the corresponding category. CoMind consistently outperforms baselines across most domains.

Category	# of Tasks	CoMind	AIDE+Code	AIDE+RAG	AIDE
Image Classification	8	<b>0.597</b>	0.459	0.434	0.525
Text Classification	3	<b>0.740</b>	0.157	0.338	0.61
Audio Classification	1	<b>0.901</b>	0.272	0.259	0.271
Seq2Seq	2	0.408	0.503	<b>0.550</b>	0.228
Tabular	4	0.664	0.673	<b>0.688</b>	0.483
Image To Image	1	<b>0.988</b>	0.932	0.617	0.568
Image Regression	1	<b>0.992</b>	0.342	<b>0.992</b>	<b>0.992</b>
All	20	<b>0.668</b>	0.469	0.510	0.512

- **Above Median:** Indicates whether the submission outperforms at least 50% of competitors on the leaderboard.
- **Win Rate:** The percentage of competitors whose final scores are lower than the agent’s score. If the agent fails to produce a valid submission, the Win Rate is 0.
- **Medals:** Medals are assigned based on the agent’s score relative to Kaggle leaderboard thresholds for gold, silver, and bronze medals.
- **Any Medal:** The percentage of competitions in which the agent earns any medal.

**Implementation Setup.** All agents use `o4-mini-2025-04-16` as their backend. Based on the settings of our main experiment, the hardware constraint is further limited to 4 vCPUs and 5 hours per competition. Each execution session is limited to 1 hour. Access to public datasets are restricted. In accordance with baselines, CoMind has access to 10 top-voted discussions and kernels.

## 6.2 RESULTS

Figure 4 shows the results. Our key findings are as follows: (i) CoMind consistently outperforms all baselines across every metric. (ii) Among the AIDE variants, AIDE+RAG outperforms AIDE+Code, and both surpass the original AIDE on most metrics, demonstrating the benefits of integrating community knowledge. CoMind further exceeds these approaches, highlighting the effectiveness of its deeper and more strategic community-aware exploration. (iii) Removing CoMind’s resource access causes a significant drop in valid submission rates and other metrics, showing that strategic access to public resources helps CoMind balance extending established methods for reliability with exploring novel approaches.

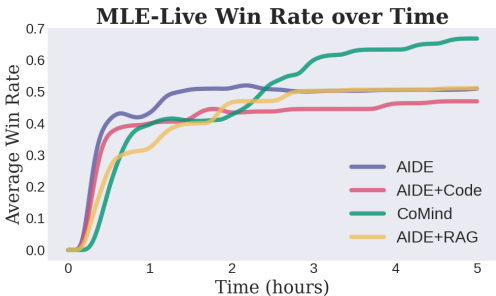


Figure 5: Win rate over time. CoMind sustains improvement while baselines plateau.

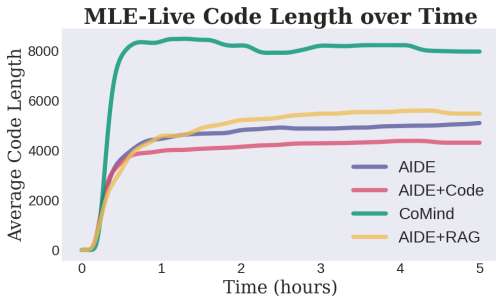


Figure 6: Code complexity over time. CoMind generates longer, richer solutions than baselines.

## 7 ANALYTICAL EXPERIMENTS

For analytical experiments, we adopt the same setup as the ablation study and evaluate model performance across multiple dimensions, including task categories, win rate over time, and code complexity.

**Task Categories** Table 2 reports the average ranks across seven task categories. CoMind outperforms all baselines in Image Classification, Text Classification, Audio Classification, and Image-to-Image tasks, highlighting its strong adaptability. We manually inspect the tasks where CoMind underperformed and find that the issues are often related to the use of large models or datasets. For example, in Seq2Seq tasks, CoMind explores complex fine-tuning strategies for large language models which often fail to complete within the one-hour runtime constraint.

**Win Rate Over Time** Figure 5 shows the evolution of average win rate over time. AIDE quickly produces concise, functional solutions, leading to a rapid rise in performance during the first hour. In contrast, CoMind spends more time on debugging and exploration early on, resulting in a slower initial improvement. However, after the first two hours, AIDE’s performance plateaus, while CoMind continues to improve through iterative refinement and deeper exploration, ultimately surpassing AIDE and achieving higher-quality solutions.

**Code Complexity** Regarding code complexity, Figure 6 illustrates the average code length during the entire competition. CoMind consistently generates significantly longer and more complex code, while other baselines begin with simpler implementations and introduce only incremental modifications. Appendix B offers a comparative analysis across code complexity metrics and task categories. Notably, CoMind’s solutions for Image Regression and Audio Classification are nearly twice as long as those of other baselines. Additionally, solutions from CoMind are, on average, 55.4% longer than those produced by AIDE.

## 8 CONCLUSION

We introduced MLE-Live, the first framework to evaluate ML agents in community-driven settings, simulating the collaborative dynamics that are essential to real-world progress in Kaggle competitions and beyond. Building upon this benchmark, we proposed CoMind, a community-augmented LLM agent that iteratively selects and synthesizes ideas, implements solutions, and shares reports within a simulated ecosystem. Our results demonstrate that CoMind not only achieves state-of-the-art performance on retrospective MLE-Bench tasks but also attains medal-level standings in live Kaggle competitions.

**Limitations and Future Work.** While our current experiments focus on Kaggle-style ML tasks, the MLE-Live framework can be extended to broader domains, such as scientific discovery, open-ended coding, or robotics, enabling research agents to contribute meaningfully across diverse fields.

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## A USE OF LLMs

We employ large language models (LLMs) exclusively for the purpose of assisting in the drafting and refinement of our manuscripts, with the objective of enhancing clarity and coherence.

## B ADDITIONAL ANALYSIS ON CODE COMPLEXITY

In this section, we provide a comprehensive analysis of the generated code using a broad set of software complexity and quality metrics, beyond mere line counts. Specifically, we report the following indicators: **Cyclomatic Complexity (CC)**, **Pylint score**, **Halstead Metrics: Volume, Difficulty, Effort**, **Source Lines of Code (SLOC)**, **Number of Comment Lines** and **Code Length**. We prioritized these over human annotation to ensure reproducibility and avoid subjective bias.

Table 3: **Code complexity and quality metrics (Cyclomatic Complexity, Pylint score, Halstead metrics, SLOC, etc.) across task categories.** CoMind produces more complex solutions compared to baselines.

Category	Metric	CoMind	AIDE	AIDE+RAG	AIDE+Code
Image Classification	CC	1.68	1.59	1.93	1.29
	Pylint Score	7.43	9.06	8.90	8.92
	Volume	330.88	143.26	84.20	175.88
	Difficulty	4.95	2.90	2.32	2.59
	Effort	1960.22	507.06	286.31	725.59
	SLOC	198.25	133.50	120.88	115.71
	Comment Lines	15.62	12.88	13.75	14.43
	Code Length	7638.40	4624.30	4701.30	5192.10
Text Classification	CC	3.58	4.28	2.00	0.00
	Pylint Score	8.82	9.09	8.89	9.26
	Volume	286.38	384.07	47.68	29.25
	Difficulty	3.76	3.94	1.25	1.31
	Effort	1183.11	2332.22	61.56	35.16
	SLOC	181.67	133.00	141.00	69.50
	Comment Lines	14.67	15.33	14.00	13.50
	Code Length	6974.70	3094.50	5920.50	5629.30
Audio Classification	CC	2.00	0.00	0.00	0.00
	Pylint Score	7.92	9.11	9.49	8.86
	Volume	718.63	244.20	115.95	227.48
	Difficulty	7.39	6.46	3.19	6.38
	Effort	5308.07	1577.11	369.58	1451.30
	SLOC	256.00	82.00	92.00	72.00
	Comment Lines	20.00	11.00	16.00	16.00
	Code Length	9449.00	3508.00	4151.00	3352.00
Seq2Seq	CC	4.38	2.25	22.33	15.75
	Pylint Score	8.58	9.04	9.14	8.51
	Volume	492.55	52.33	390.46	324.00
	Difficulty	3.87	2.14	5.26	3.68
	Effort	1935.02	140.58	2083.84	1686.74
	SLOC	184.50	63.50	222.50	147.50
	Comment Lines	22.50	13.00	23.00	19.50
	Code Length	6925.50	5649.50	8357.50	2728.50
Tabular	CC	2.78	1.62	2.38	0.25
	Pylint Score	8.65	8.96	8.87	9.31
	Volume	1264.61	856.12	815.29	435.46
	Difficulty	7.37	4.83	6.05	3.69
	Effort	10 808.93	6163.62	5564.22	2001.06
	SLOC	218.75	139.75	147.50	93.50
	Comment Lines	18.25	14.75	15.25	10.50
	Code Length	8570.00	3534.00	6064.00	5759.80

Category	Metric	CoMind	AIDE	AIDE+RAG	AIDE+Code
Image to Image	CC	1.72	2.00	3.00	1.88
	Pylint Score	8.43	6.25	6.64	7.74
	Volume	1298.11	1481.62	414.59	431.08
	Difficulty	9.68	6.73	3.94	3.79
	Effort	12 565.66	9967.24	1633.22	1631.93
	SLOC	228.00	175.00	121.00	128.00
	Comment Lines	26.00	8.00	23.00	13.00
	Code Length	8800.00	5231.00	4815.00	6671.00
Image Regression	CC	1.68	2.00	2.40	2.00
	Pylint Score	8.62	8.75	8.80	8.89
	Volume	1310.92	241.08	70.32	72.00
	Difficulty	8.75	3.88	2.18	2.73
	Effort	11 466.58	934.17	153.43	196.36
	SLOC	267.00	145.00	116.00	133.00
	Comment Lines	36.00	15.00	12.00	12.00
	Code Length	10 991.00	4841.00	4655.00	5614.00

## C TOKEN USAGE ON MLE-BENCH COMPETITIONS

Agent	Uncached Tokens	Cached Tokens	Completion Tokens	Cost
CoMind	18.23 M $\pm$ 14.62 M	13.05 M $\pm$ 11.43 M	1.96 M $\pm$ 1.04 M	\$32.25 $\pm$ 19.43

Table 4: Average token usage (mean  $\pm$  standard deviation) and monetary cost for CoMind across the 75 Kaggle competitions in MLE-Bench. The cost is calculated based on the API prices of o4-mini published by OpenAI.

## D LOCAL EVALUATION DYNAMICS OF CoMIND ON ONGOING COMPETITIONS

Figure 7 plot the agent’s locally estimated validation metrics over its execution time, as computed by the Evaluator module using held-out validation splits constructed from the public training data. These trajectories capture how CoMind iteratively explores, implements, debugs, and refines solution pipelines through its multi-agent workflow. It illustrates several consistent patterns: (i) rapid early improvements as baseline solutions are assembled; (ii) mid-phase refinements driven by Analyzer-guided idea selection and iterative debugging; and (iii) late-stage stabilization once the agent converges to high-performing configurations.

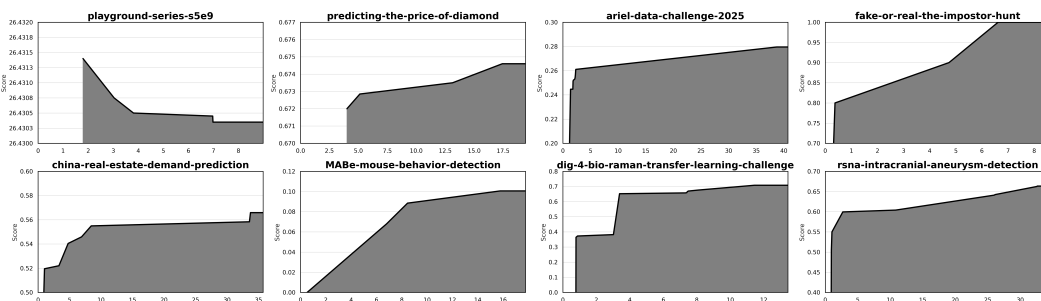


Figure 7: Evolution of CoMind’s Locally Estimated Competition Metrics Over Runtime Across Eight Ongoing Kaggle Tasks.

## E CATEGORIES AND DIFFICULTIES IN MLE-BENCH

MLE-Bench (Chan et al., 2025) curates 75 ML engineering-related competitions from Kaggle, creating a diverse set of challenging tasks that test real-world ML engineering skills. These competitions span 15 diverse problem categories. Each competition has an associated description, dataset, and grading code. MLE-Bench categorizes competitions based on human evaluation results: Low (29%) if an experienced ML engineer can produce a sensible solution in 2 hours (excluding training time), Medium (51%) for 2–10 hours, and High (20%) for more than 10 hours.

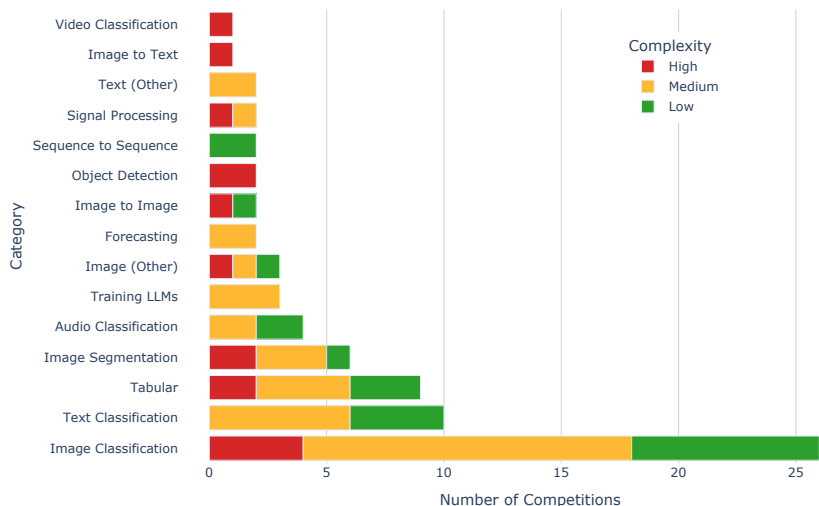


Figure 8: (From MLE-Bench) **Competitions in MLE-Bench spans 15 categories.** MLE-Bench categorizes competition difficulties in Low, Medium and High.

## F COMIND ON COBENCH

To directly assess CoMind’s extensibility beyond Kaggle-style environments, we conducted an additional experiment on CoBench (Sun et al., 2025), a dataset of 36 combinatorial optimization problems that is structurally different from Kaggle competitions and does not involve notebooks, discussions, or leaderboard dynamics. Using gpt-5-mini as a shared backbone, we compared CoMind (without access to public resources) against AIDE (Jiang et al., 2025), FunSearch (Romera-Paredes et al., 2024), and Greedy Refinement (iteratively prompting the LLM to refine the current best solution). Following the settings of CoBench, each agent operates through 64 research steps, receiving feedbacks on a test set at each step and has a 10-second execution time limitation. Across 9 representative CoBench tasks, CoMind’s normalized score achieves competitive performance and, on average, outperforms the baselines, as shown in Table 5.

## G MLE-LIVE ON MLE-BENCH COMPETITIONS

We collected all public kernels and discussions posted before each competition’s deadline, preserving the temporal information to simulate realistic research environments. Table 6 presents detailed statistics for each competition in MLE-Live. The dataset encompasses 15,733 kernels and 12,951 discussions across competitions of varying difficulty levels (Low, Medium, High).

Figure 9 shows the distribution of kernel votes across all competitions. The distribution is heavily skewed, with over half of the kernels receiving fewer than 10 votes. This long-tail pattern reflects real-world community dynamics where a small fraction of high-quality contributions attracts substantial attention, while most submissions receive minimal engagement.

Task	CoMind	AIDE	FunSearch	Greedy Refinement
Crew scheduling	<b>0.915</b>	0.448	0.546	0.602
Graph colouring	0.879	0.850	0.893	<b>0.968</b>
Constrained guillotine cutting	0.975	0.911	<b>0.993</b>	0.989
MIS	0.909	<b>0.932</b>	0.860	0.874
Aircraft landing	<b>0.865</b>	0.863	0.760	0.378
Bin packing (1D)	0.903	0.925	<b>0.975</b>	0.821
Euclidean Steiner problem	0.690	0.636	0.701	<b>0.760</b>
Set covering	<b>0.922</b>	0.887	0.918	0.916
TSP	<b>0.923</b>	0.606	0.860	0.832
<b>Avg</b>	<b>0.887</b>	0.784	0.834	0.793

Table 5: Evaluation on 9 representative task of CoBench.

Table 6: **Statistics of MLE-Live on MLE-Bench competitions.** *Kern.* is the number of public kernels. *Disc.* is the number of discussions. *Dsets* is the number of external datasets referenced by public kernels, *Lines* refers to the average number of lines of all kernels, *Comms* is the average number of comments in all discussions.

Competition	Kern.	Disc.	Dsets	Lines	Comms
<b>Low</b>					
aerial-cactus-identification	275	27	12	177.40	3.52
aptos2019-blindness-detection	186	503	70	357.18	8.33
denoising-dirty-documents	59	19	1	70.36	4.53
detecting-insults-in-social-commentary	0	27	0	–	4.26
dog-breed-identification	64	33	9	161.75	5.15
dogs-vs-cats-redux-kernels-edition	0	31	0	–	4.68
histopathologic-cancer-detection	118	51	12	228.19	9.53
jigsaw-toxic-comment-classification-challenge	128	394	56	80.88	7.19
leaf-classification	803	23	1	143.37	1.61
mlsp-2013-birds	0	35	0	–	4.94
new-york-city-taxi-fare-prediction	143	53	6	256.69	5.75
nomad2018-predict-transparent-conductors	53	40	9	57.14	5.30
plant-pathology-2020-fgvc7	207	91	27	281.84	5.14
random-acts-of-pizza	8	19	1	35.25	3.74
ranzcr-clip-catheter-line-classification	323	289	156	326.17	6.99
siim-isic-melanoma-classification	276	707	135	345.59	10.87
spooky-author-identification	153	68	13	103.45	3.75
tabular-playground-series-dec-2021	427	134	53	233.22	6.84
tabular-playground-series-may-2022	247	64	23	273.53	5.02
text-normalization-challenge-english-language	57	51	3	153.93	4.45
text-normalization-challenge-russian-language	12	20	2	37.67	2.85
the-icml-2013-whale-challenge-right-whale-redux	0	8	0	–	1.62
<b>Medium</b>					
AI4Code	159	178	93	395.78	5.76
alaska2-image-steganalysis	109	154	31	317.38	6.35
billion-word-imputation	0	23	0	–	3.43
cassava-leaf-disease-classification	411	724	209	358.37	6.77
cdiscout-image-classification-challenge	91	109	3	57.10	9.25
chahi-hindi-and-tamil-question-answering	269	147	137	341.48	6.74
champs-scalar-coupling	290	340	49	307.36	8.54
facebook-recruiting-iii-keyword-extraction	0	72	0	–	5.32
freesound-audio-tagging-2019	109	128	18	349.46	7.23
google-quest-challenge	225	258	128	442.04	9.04
h-and-m-personalized-fashion-recommendations	419	223	63	240.76	6.30

Continued on next page

Competition	Kern.	Disc.	Dsets	Lines	Comms
herbarium-2020-fgvc7	19	15	3	205.83	3.67
herbarium-2021-fgvc8	21	26	17	266.86	2.46
herbarium-2022-fgvc9	36	37	6	274.52	3.84
hotel-id-2021-fgvc8	30	30	15	196.00	2.07
hubmap-kidney-segmentation	321	340	178	325.47	6.70
icecube-neutrinos-in-deep-ice	187	156	38	319.70	5.58
imet-2020-fgvc7	32	21	13	298.37	3.67
inaturalist-2019-fgvc6	12	11	3	244.17	4.27
iwildcam-2020-fgvc7	21	22	5	256.86	3.55
jigsaw-unintended-bias-in-toxicity-classification	410	413	118	301.86	8.16
kuzushiji-recognition	42	55	4	226.57	5.00
learning-agency-lab-automated-essay-scoring-2	477	226	301	349.24	7.78
lmsys-chatbot-arena	305	260	123	299.33	8.51
multi-modal-gesture-recognition	0	39	0	-	3.36
osic-pulmonary-fibrosis-progression	513	499	80	386.23	5.92
petfinder-pawpularity-score	397	461	153	240.50	5.86
plant-pathology-2021-fgvc8	325	112	135	273.29	4.20
seti-breakthrough-listen	230	222	72	333.81	7.82
statoil-iceberg-classifier-challenge	160	178	15	80.98	6.09
tensorflow-speech-recognition-challenge	47	139	4	55.94	6.83
tensorflow2-question-answering	102	193	52	420.29	6.71
tgs-salt-identification-challenge	213	336	24	329.40	12.16
tweet-sentiment-extraction	536	387	117	324.96	9.86
us-patent-phrase-to-phrase-matching	456	233	352	284.25	7.15
uw-madison-gi-tract-image-segmentation	233	230	124	445.30	6.32
ventilator-pressure-prediction	407	268	70	246.07	9.05
whale-categorization-playground	32	22	4	61.93	5.00
<b>High</b>					
3d-object-detection-for-autonomous-vehicles	39	116	10	565.09	6.19
bms-molecular-translation	167	218	57	463.33	10.39
google-research-identify-contrails-reduce-global-warming	143	136	115	322.43	6.24
hms-harmful-brain-activity-classification	631	390	258	573.88	6.64
iwildcam-2019-fgvc6	37	26	9	196.06	3.77
nfl-player-contact-detection	94	81	32	342.78	4.17
predict-volcanic-eruptions-ingv-oe	102	55	21	271.21	3.55
rsna-2022-cervical-spine-fracture-detection	209	152	106	302.68	4.34
rsna-breast-cancer-detection	538	433	291	342.78	7.11
rsna-miccai-brain-tumor-radiogenomic-classification	414	334	131	321.36	5.72
siim-covid19-detection	586	419	382	337.11	5.59
smartphone-decimeter-2022	49	56	16	244.82	3.79
stanford-covid-vaccine	201	194	29	342.38	8.55
vesuvius-challenge-ink-detection	190	177	72	387.63	6.19
vinbigdata-chest-xray-abnormalities-detection	317	187	115	379.55	6.70

## H ERROR ANALYSIS

In this section, we analyze why CoMind failed to surpass the strongest public kernel in the `fake-or-real-the-impostor-hunt` Kaggle competition. The task involves identifying the fake text within each pair of samples. Although the dataset originates from The Messenger journal, both the “real” and “fake” texts have been heavily modified by LLMs, making the distinction more subtle and challenging. Below, we summarize the main obstacles encountered during CoMind’s execution:

**Noised external resources.** Public voting did not reliably indicate kernel quality; many highly upvoted kernels were merely ensembles or reused outputs from stronger solutions, offering little actionable insight. With a large volume of heterogeneous public contributions, identifying genuinely informative resources remained difficult.

**Sparse evaluation signal.** CoMind depends on the Evaluator’s feedback to guide iteration, but the task’s extremely small dataset allowed validation on only 10 examples. This produced highly unstable feedback and limited the system’s ability to differentiate between small performance variations. As shown in Figure 7,

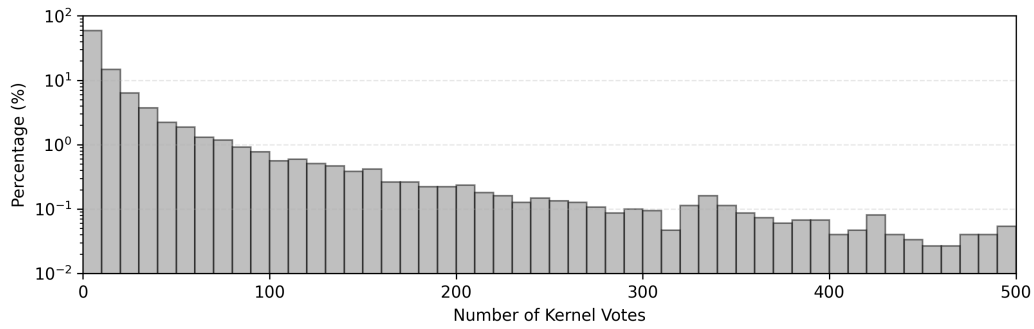


Figure 9: **Distribution of kernel votes across all competitions in MLE-Bench.** Over half of the kernels received fewer than 10 votes, demonstrating the long-tail nature of community contributions where most submissions receive minimal engagement while a small fraction attracts substantial attention.

Evaluator accuracy saturated at 100% within the first 7 hours, leaving no meaningful gradient for further improvement.

**Insufficient ablation analysis.** While CoMind explored multiple strategies, its assessment of individual module effectiveness was inconsistent. For example, early iterations attempted to fine-tune local LLMs via LoRA and train binary classifiers on their outputs, but due to poor base model selection and insufficient hyperparameter exploration, these approaches underperformed simple classical signals such as TF-IDF cosine similarity and token-level similarity.

## I PROMPTS AND RESPONSES FOR COMIND

This section provides some examples of prompts and responses in CoMind, including **Coordinator**, **Analyzer**, **Idea Proposer**, **Coding Agent** and **Evaluator**.

### I.1 COORDINATOR

#### Prompt for Solution Draft Synthesis

**Introduction** You are an expert machine learning researcher preparing for the Kaggle competition described below.

**Task Description** {description of the specified task}

**Ideas** {entries in the idea pool}

**Reports** {entries in the report pool}

**Public Pipelines** {all public pipelines extracted before}

#### Goals

1. Carefully read the reports provided above.
2. Based on the ideas and reports, propose {num\_pipes} **promising self-contained pipelines** that are likely to perform well.
3. The Public pipelines section contains top-ranked public pipelines during the competition. Use them as reference to polish your pipelines.
4. Each pipeline should not overlap with others. Your proposed pipelines should include **one baseline pipeline that uses well-known methods but is robust and relatively easy to implement**. You should reinforce public pipelines and previous pipelines based on their reports (if provided).
5. Ensure that each pipeline can be trained within 2 hours on a single A6000 with 48GB memory.
6. Read the **submission format** requirements in the task description carefully. The format requirement is possible to be different from the training dataset. **THIS IS EXTREMELY IMPORTANT**. Mention in the pipeline descriptions and be sure to include the code that handles the input and output.
7. DO NOT USE tensorflow, use pytorch instead

#### Response Template for Solution Draft Synthesis

**Submit Pipelines** Descriptions and codes of pipelines, separated each pipeline by ===SEPARATOR=== mark. For each pipeline, attach code that captures its essential. **You must include the code in public pipelines that handles input and output, and if there are parts of the public pipelines that are similar to the current pipeline, you should include them as well.**

### I.2 ANALYZER

**Prompt for Strategy Distillation**

**Introduction** You are an expert machine learning researcher preparing for the Kaggle competition described below.

**Task Description** {description of the specified task}

**Goals** These are top-ranked public scripts during the competition. Your job is to:

1. Carefully read the following scripts.
2. For each script, if it's self-contained, i.e., including model architecture (if there's a model), training strategies, evaluation, etc., then summarize its pipeline.
3. If the pipeline contains technical details, such as extensive feature engineering, hyperparameter tuning, etc., then list them in full detail.
4. Select a representative code segment for each pipeline. You must include dataset reading / submission generation parts. If task-specific details such as feature engineering are included, the code segment should contain them as well.

**Public Kernels** {contents of public kernels}

**Response Template of Strategy Distillation of Public Kernels**

**Pipelines** Description of each strategy, separated by ===SEPARATOR=== mark. For each strategy, follow this format:

- Pipeline: A full detailed description of the pipeline. All input/output format, hyperparameters, training settings, model architectures, feature engineering, validation metric, and any other relevant information should be included. **Do not omit any feature engineering details.**
- Code abstract: A representative code segments that captures the essence (including input/output) and novelty of the pipeline. You **MUST** go through all the publicly available code and **include the parts that generate the submission file.** Contain task-specific engineering details. Mark the remainder as ellipses.

**Prompt for Strategy Distillation of Public Discussions**

**Introduction** You are an expert machine learning researcher preparing for the Kaggle competition described below.

**Task Description** {description of the specified task}

**Goals** These are top-voted public discussions during the competition. Your job is to:

**Public Discussions** {contents of public discussions}

1. Carefully read the following discussions.
2. For each discussion, you should decompose it into critical, novel and inspiring ideas that have potential to win this competition.

**Response Template of Strategy Distillation of Public Discussions**

**Ideas** required format: python list of strings, each element is a description of an idea extracted from the discussions. e.g. ['idea 1', 'idea 2'].

## I.3 IDEA PROPOSER

**Prompt for Brainstorm**

**Introduction** You are an expert machine learning researcher preparing for the Kaggle competition described below.

**Task Description** {description of the specified task}

**Goals** I already have a list of ideas that partially explore how to approach this competition. Your job is to:

1. Think creatively and construct at least **4 alternative and highly novel solution paths** that are likely to perform well, especially if combined with careful experimentation.
2. Each solution path can be a strategy, pipeline, or method that combines multiple techniques. Try to make them as different as possible from the existing "ideas" list.

3. After describing each full solution path, **break it down into individual minimal ideas**- these should be the smallest units of implementation (e.g., "use LightGBM for baseline", "normalize input features", "apply stratified K-fold CV")
4. Ensure these ideas do not substantially duplicate items already in "ideas".
5. Refer to the "Reports" section for the latest updates and suggestions on the ideas and previous pipelines.

**Ideas** {entries in the idea pool}

**Reports** {entries in the report pool}

**Public Pipelines** {all public pipelines extracted before}

**Instructions** Format your output like this (one line, one idea):

{your understanding of the task and explanation of your approaches}

===SOLUTION\_PATH.1===

{description of this approach}

- {minimal idea 1}

- {minimal idea 2}

- {minimal idea 3}

- ...

===SOLUTION\_PATH.2===

...

===SOLUTION\_PATH.3===

...

Be ambitious but realistic - many ideas can later be tested on a small subset of the data. Focus on novelty, diversity, and decomposability. Ready? Start.

### Prompt for Idea Filtering and Reconstruction

**Introduction** You are a machine learning expert. After carefully searching the relevant literature, you have come up with a list of ideas to implement. However, this idea list has some issues:

- Some ideas are too similar and should be merged into one.
- Some ideas are overlapping, you should rephrase and decouple them.
- You should discard ideas that are irrelevant to the final performance, such as error visualization, etc.

You should refer to the Reports section and Public Pipelines section for previous implemented pipelines. Please decompose, merge, and reconstruct the ideas listed below.

**Ideas** {entries of the idea pool}

**Reports** {entries of the report pool}

**Public Pipelines** {all public pipelines extracted before}

### Response Template of Idea Filtering and Reconstruction

**Ideas** required format: Python list of strings, each element is a description of an idea. e.g. ['idea 1', 'idea 2'].

### Prompt for Coding Agent Report Compilation

Please summarize the results and submit a comprehensive report.

### Response Template for Coding Agent Report Compilation

**pipeline** A detailed description of the pipeline that generated the best results. All hyperparameters, training settings, model architectures, feature engineering, validation metric, and any other relevant information should be included. Describe potential improvements and future work.

**summary** A comprehensive evaluation of each individual component of the pipeline. For each component, summarize in the following format:

=== {name of the component} ===

**Novelty:** 0-10 (0: trivial, 10: clearly novel - major differences from existing well-known methods)  
 {your rationale}  
**Feasibility:** 0-10 (0: almost impossible to implement and require extensive engineering, 10: Easy to implement)  
 {your rationale}  
**Effectiveness:** 0-10 (0: minimal performance improvement, 10: very strong performance, significantly outperform most baselines)  
 {your rationale}  
**Efficiency:** 0-10 (0: very slow, over-dependent on CPU and hard to produce meaningful results within the time limit, 10: high utilization of GPU)  
 {your rationale}  
**Confidence:** 0-10 (0: no empirical results, not sure whether the evaluation is correct, 10: fully verified on large scale with abundant results)

#### I.4 EVALUATOR

##### Prompts for Dataset Splitting and evaluate.py

You are an experienced machine learning engineer. Please generate two self-contained Python code for local evaluation of a Kaggle agent. Your code should be robust, reusable, accept command-line arguments and print necessary information.

##### Background

- Kaggle competitions usually provide labels only for the training set. To evaluate an agent locally, we need to split the training set into a training and validation split.
- The validation set must hide its labels from the agent. The agent only sees the training set (with labels) and the validation inputs (without labels).
- The hidden validation labels will be stored separately and used only for offline evaluation.
- Importantly: `./public` must never contain validation labels. Validation labels are saved only in `./private`.

**Kaggle Competition Description** {description of the specified task}

**Data Preview** {schema of the input file structure}

**Deliverables** Please generate two scripts (both in Python 3, runnable from the command line):

##### 1) split\_dataset.py

**Goal:** Split the original training data into 90% training and 10% validation. Store validation inputs (without labels) in `./public`, and validation labels in `./private`. The training set (with labels) and original test set must remain in `./public`, preserving the original structure as closely as possible. The structure of validation inputs should also match the test set. Generate a sample validate submission `validate_sample_submission.csv` under `./public`. All original data (training and test) are visible in {path to the input directory}.

**Example:** If the original data is structured as:

```
- kaggle_evaluation/ (official evaluation tool provided by Kaggle)
  - __init__.py
  - ...
- train.csv
- train/
- test.csv
- test/
- sample_submission.csv
```

You should split the dataset into:

```
(./public/)
- kaggle_evaluation/ (official evaluation tool provided by Kaggle) (unchanged, soft
  links)
  - __init__.py
  - ...
- train.csv (this contains 90% of the training data)
- train/ (this contains 90% of the training data, keep unchanged data as soft links)
- test.csv (unchanged, soft link)
- test/ (unchanged, soft link)
- sample_submission.csv (unchanged, soft link)
- validate.csv (this contains 10% of the training data with labels withheld)
- validate/ (soft links)
- validate_sample_submission.csv (a sample submission file for validation set)
```

```
(./private/)
- validate.csv (labels of validation set)
```

If the training data contains zip files, you should extract them to the public directory before splitting the dataset. You should always print the directory structure after the split. Do not extract files to the original directory and keep it unchanged.

If the training data contains multiple classes, you should use **stratified sampling**. You should strictly follow the evaluation metric mentioned in the task description and ensure the validation set is representative of the overall class distribution. Never write validation labels into `./public`.

Your code will be executed by command line as follows:

```
```bash
python split_dataset.py --input_dir <path to the input directory> --public_dir ./public
  --private_dir ./private
```
```

DO NOT store the training and test files in other folders such as `./public_*`, the `./public` folder will be exposed to later code agent. Make sure the `./public` directory has similar structure with the original data folder.

## 2) evaluate.py

Goal: Evaluate the agent's predictions on validation set against the hidden ground truth (`./private/...`). Output evaluation results (json format) to console and write `./private/eval_report.json`.

It will be executed by command line as follows:

```
```bash
python evaluate.py --public_dir ./public --private_dir ./private --pred <path to the
  validation submission file>
```
```

We will pass the path to the sample validation submission file as the argument to your `evaluate.py` script. It typically produces low scores.

The script should generate in the following json format at `./private/eval_report.json`:

```
{
  "score": A float number represents the evaluation score on the validation set. Do
    not omit this field. If the evaluation is unsuccessful or the predictions are
    invalid, this field should be set to null,
  "success": A boolean value indicates whether the evaluation was successful or not,
  "message": A string provides additional information about the evaluation result.
    Leave it an empty string if the predictions are valid and evaluation is
    successful. Otherwise provide necessary details on why it failed.
}
```

Do not raise any error or exception. If the evaluation is unsuccessful, you should set the score to null and provide a detailed explanation in the message field.

Now, let's write these two scripts step by step. You should first generate `split_dataset.py`. We will execute the code by command line as mentioned above. You should correct the code in case of any issues. You should always generate full, self-contained code. No part of the code should be omitted.

Respond in the following format:

```
```current_file
This should be either split_dataset.py or evaluate.py. Leave this as None if both are
  generated and functioned. This indicates the current file you are editing.
```

```explanation
You explanation on the workflow of your code.
```

```python
The full content of the current file. Leave this as None if both are generated and
  functioned.
```
```

## I.5 CODING AGENT

## Prompts for Coding Agent Iterative Implementation

**Introduction** You're an expert Kaggle competitor tasked with implementing a pipeline into Python code. You can modify the details (training parameters, feature engineering, model selection, etc. ), but do not change overall architecture of this pipeline. The goal is to **obtain best score** on this competition.

**Task Description** {description of the specified task}

**Pipeline** {description of the solution draft to implement}

**Data Overview** {schema of the input file structure} Follow the pipeline description and the code abstract to implement it. All the input files are visible in ./input folder, this folder typically contains the competition data and external resources, including public datasets, models and outputs of other kernels. DO NOT USE /kaggle/input paths in your code. USE ./input instead. file structure:

```
- input/ (./input)
  - competition_id/ # the official competition dataset
  - alice/dataset1/ # other public datasets
  - alice/kernel1/ # referenced kernels
- working/
  - agent.ipynb # the notebook you will be working on (./agent.ipynb)
  - other files
```

You will develop the pipeline based on this codebase. Any output files of the codebase, such as csvs, checkpoints, etc., are visible in ./, which is also your current working directory.

{Description of Selected Codebase}

You should note that checkpoints generated by this codebase is store in ./ other than ./input. You must load the checkpoint file under the ./ directory for ensemble prediction.

Your code must produce a submission at ./submission.csv, this is EXTREMELY IMPORTANT. Before generating the submission, you must print the value of the evaluation metric computed on a hold-out validation set. You can use custom evaluation functions during training, but the final metric **MUST FOLLOW THE EVALUATION SECTION IN THE TASK DESCRIPTION** on a validation set.

If other kernels with submission.csv are provided in the input folder, you can ensemble them before generating your own submission. This is important because we will pick your best code based on this metric. You are allowed to load the checkpoints of other models. Do not contain any absolute paths in your code. Time limit per run is 2 hours. Your code will be killed if timeout.

Your code will be executed on a single A6000 GPU. Use large batchsizes to maximize the gpu utilization. If the code segment is provided in this prompt, you should follow the input/output structure. You are allowed to install any packages you need or inspect the workspace (e.g., print file contents, check folder structure). Always use gpu for acceleration. DO NOT USE ABSOLUTE PATHS IN YOUR CODE.

The workspace will be maintained across iterations. That is, if your first iteration code produces a checkpoint, you can load it in the second iteration. You can ensemble submissions generated by yourself and other kernels. You should generate model checkpoints for future loading. If you load the external submissions successfully but failed to merge them with your own predictions, you should print the headers of the external submission and your own predictions and check if the ids are aligned. All the external submissions are valid. Your predictions should be in the same format as them.

To evaluate your submission locally. You should also generate a submission file on the validation set. All the validation data are typically structured similarly to the test data. An external grader will be used to evaluate your validation submission. That is to say, you should generate TWO submission files: one is for the validation set and the other is for the test set. Generate two submission files in the same code cell.

You are allowed to install any packages by running 'pip install ;package\_name;' in your script. Your installation will take effect in the NEXT cell.

A persistent Jupyter Notebook session is maintained. Your proposed code cell will be directly appended to the notebook and executed. You should separate data loading, training and evaluation in different cells. Now, please propose THE FIRST CELL of your code (not your full code!) using the following format:

```
<goal>
The explanation of your first cell. You should describe the desired execution time and
output of this cell. Explain how to interpret the execution output.
</goal>

<code>
The content of this cell. Do not wrap the code in a markdown block. Your code will be
appended to the notebook, which is stored at ./agent.ipynb. Your code must print
necessary information after each milestone.
```

```
</code>
```

```
<validation_submission>
```

The name of the submission file for the validation set. e.g. validate\\_submission.csv.  
If your current code cell does not produce two submission files, leave this as None.

```
</validation_submission>
```

```
<submission>
```

The name of the submission file for the test set. e.g. submission.csv. This submission should be ready for Kaggle submission. If your current code cell does not produce two submission files, leave this as None.

```
</submission>
```

The validation\\_submission tag and the submission tag should must be both empty or both non-empty.

### Prompt for Execution Monitor

You are an AI assistant monitoring code execution. Your task is to analyze the current execution output and decide whether the code should continue running.

Code being executed:

{code to analyze}

Goal: {execution target of this code}

Runtime Information:

- Current runtime: {code execution time elapsed}
- Maximum runtime: {maximum execution time}
- Remaining time: {remaining execution time}

Current Output:

{current output of this code cell}

Consider these factors:

1. Is the loss exploding (becoming very large or NaN)?
2. Is the loss decreasing normally over time?
3. Are there any error messages indicating failure?
4. Does the output suggest normal training/execution progress?
5. Based on current progress and remaining time, is it possible to complete within the time limit?

Respond in the following format:

```
<action>
CONTINUE/STOP
</action>
```

```
<explanation>
```

Your rationale for the action. Describe the current progress, your estimated remaining time, and explain why you think the execution should continue or stop. DO NOT GIVE SUGGESTIONS ON BUG FIXES.

```
</explanation>
```

### Prompt for Consequent Code Revisions

The execution takes {execution\_time} seconds and ends with the following output:

{truncated output}

Execution completed successfully. You should keep updating your code (e.g., try different hyperparameters, augmentations, model architectures) after you have made successful submission. Your best submission will be recorded.

Now, respond in the following format:

```
<validation_submission>
```

The name of the submission file for the validation set. e.g. validate\\_submission.csv.

If your current code cell does not produce a submission file on the validation set, leave this as None.

```
</validation_submission>
```

```
<submission>
```

```
The name of the submission file for the test set. e.g. submission.csv. This submission
  should be ready for Kaggle submission. If your current code cell does not produce
  a submission file on the test set, leave this as None.
</submission>
```

```
<goal>Describe the goal and how to inspect the output of your next code cell</goal>
```

```
<code>
```

```
The content of your next code cell. Following the previous format, do not wrap your
code within markdown code marks. You should keep updating your code (e.g., try
different hyperparameters, augmentations, model architectures) even after you have
made successful submission. Always evaluate your submission and print the metric
on a validation set.
```

```
</code>
```

The validation\_submission tag and the submission tag should must be both empty or both non-empty.





```

- Writes out background images as PNG.
- Code abstract:
  for(i in 1:4) {
    matches=seq(1,205,by=12)+(i-1)*3
    rawData=matrix(0,258*540,length(matches))
    for(j in seq_along(matches)){
      imgY=readPNG(file.path(testDir,paste0(matches[j],'.png')))
      rawData[,j]=as.vector(imgY[1:258,1:540])
    }
    background=matrix(apply(rawData,1,max),258,540)
    writePNG(background, paste0('background',matches[j],'.png'))
  }
  ...
----- PIPELINE SEPARATOR -----
Public pipeline (2): - Pipeline: Pixel-wise Random Forest regression (Python, chunk size=1e6).
- Feature engineering: pad image by mean value (padding=1); extract 3*3 neighborhood per
  pixel, flatten as features.
- Training data: load all train noisy images, compute features via joblib parallel (n_jobs
  =128), load targets as flattened clean pixel intensities/255.
- Model: sklearn.ensemble.RandomForestRegressor(warm_start=True, n_jobs=-1). Incrementally
  add one estimator at a time: split training rows into CHUNKSIZE=1e6 slices, in each
  slice increase n_estimators by 1 and fit on that slice.
- Prediction: extract test features similarly, generate index strings "image_row_col",
  predict pixel values, write submission CSV.
- Code abstract:
  def get_padded(img, padding=1):
    padval=int(round(img.mean()))
    ... return padded
  def get_features_for_image(img, padding=1):
    padded=get_padded(img, padding)
    return np.vstack([padded[i:i+3, j:j+3].reshape(1,-1)
                      for i in range(rows) for j in range(cols)])
  ...
  def get_model(X,y):
    model=RandomForestRegressor(n_estimators=0, warm_start=True, n_jobs=-1)
    for start,end in slices:
      model.set_params(n_estimators=model.n_estimators+1)
      model.fit(X[start:end],y[start:end])
    return model
  ...
----- PIPELINE SEPARATOR -----
... (omitted) ...
----- PIPELINE SEPARATOR -----
Public pipeline (9): - Pipeline: XGBoost with basic features in R.
- Features: raw pixel value, kmeansThreshold binary, backgroundRemoval feature.
- Sample 25k pixels, build DMatrix, 5-fold CV, early stop, select rounds, train xgb.
- Predict on test, clip, build id strings, write submission.csv.
- Code abstract:
  dat=cbind(y,raw=img2vec(imgX),thresholded=kmeansThreshold(imgX),
            backgroundRemoval=img2vec(backgroundRemoval(imgX)))
  rows=sample(nrow(dat),25000)
  dtrain=xgb.DMatrix(dat[rows,-1],label=dat[rows,1])
  xgb.tab=xgb.cv(data=dtrain,nfold=5,early.stop.round=50)
  xgb.mod=xgboost(data=dtrain,nrounds=min.err.idx)
  yHat=predict(xgb.mod,newdata=as.matrix(x))
  ...

```

Then, the Idea Proposer begins brainstorming to propose more original strategies.

```

===SOLUTION_PATH_1===
Multi-Scale Wavelet-U-Net with Attention and Multi-Term Loss
Description: decompose each image via discrete wavelet transform (DWT) into low-/high-
  frequency bands, process each band in a dual-branch U-Net enhanced with channel- and
  spatial-attention, then invert the wavelet to reconstruct. Train end-to-end with a
  weighted sum of pixel-wise RMSE, wavelet-band consistency, and edge preservation losses.
- apply 2D DWT to noisy input -> obtain LL, LH, HL, HH sub-bands
- feed LL into a "coarse" encoder branch, feed concatenated LH/HL/HH into a "detail" encoder
  branch
- use a U-Net decoder to upsample each branch back to patch size, fuse via learned 1*1
  convolutions
- insert Convolutional Block Attention Modules (CBAM) after each encoder and decoder block
- define loss = alpha*pixelRMSE(clean,output) + beta*bandRMSE(wavelet(clean),wavelet(output))
  + gamma*edgeLoss(Sobel(clean),Sobel(output))
- train on full images with AdamW and a cosine-annealing LR schedule

===SOLUTION_PATH_2===
Stroke-Aware Conditional GAN with OCR-Guided Perceptual Loss
Description: build a conditional GAN (generator = deep residual encoder-decoder, discriminator
  = PatchGAN) that not only minimizes pixel loss but also preserves text strokes-enforce a
  stroke-level loss via a pre-trained small CNN classifier that predicts presence/width of

```

strokes. Add an OCR-based perceptual loss: feed predictions through a frozen OCR engine embedding and minimize distance to clean embedding.

- implement generator as ResNet blocks + skip connections (64->128->256->128->64)
- implement discriminator as 70\*70 PatchGAN to focus on local texture
- include L1 pixel loss + adversarial loss + stroke consistency loss (L1 between stroke-CNN features on clean vs. restored)
- freeze a small text-structure CNN (trained on binary masks) to extract stroke features
- run Tesseract (or lightweight OCR CNN) on restored vs. clean, extract penultimate-layer activations, add perceptual loss term
- train with R1 gradient penalty and spectral normalization on discriminator

===SOLUTION\_PATH\_3===  
 Joint Dictionary Learning + Non-Local Patch Aggregation  
 Description: learn paired dictionaries (D\_noisy, D\_clean) for small patches (e.g. 8\*8) via coupled K-SVD. At test time, extract overlapping patches, compute sparse codes alpha under D\_noisy via OMP, reconstruct clean patches = D\_clean\*alpha. Then, perform non-local means on the reconstructed patches to exploit self-similarity and average aggregates.

- sample a large bank of noisy/clean patch pairs, initialize D\_noisy, D\_clean with DCT basis
- run coupled K-SVD to minimize  $\|D_{noisy} * \alpha - y_{noisy}\| + \|D_{clean} * \alpha - y_{clean}\|$  w.r.t. D\_noisy, D\_clean, alpha
- at test time, for each image patch y\_noisy, compute alpha via Orthogonal Matching Pursuit ( sparsity <= k)
- reconstruct y\_clean\_est = D\_clean\*alpha for each patch
- perform block-matching to find K nearest patches per reference patch (Euclid dist), stack them
- aggregate reconstructed patches with non-local weights (e.g. Gaussian on reconstruction residual)

===SOLUTION\_PATH\_4===  
 Self-Supervised Blind Denoising via Noise2Void + Test-Time Adaptation  
 Description: exploit purely noisy data-train a small U-Net with masked pixel prediction ( Noise2Void) on each test image at inference (test-time training). The network learns to predict a pixel from its context, gradually adapting to local noise statistics, then you run a forward pass to obtain the cleaned image. No clean target needed.

- define blind-spot or random masking scheme: mask 1% pixels per batch, replace with neighbors
- build a lightweight CNN (e.g. 5 down/up blocks with skip connections) that predicts a full image
- fine-tune this CNN on each test image for N\_iter (e.g. 500 steps) using only masked L2 loss
- use data augmentation (rotations, flips) on the single test image to diversify contexts
- after adaptation, perform a clean forward pass without masking to get the denoised output
- optionally ensemble outputs from multiple random initializations to reduce variance

To remove similar ideas and decompose overlapped ideas, a reconstruction is performed subsequently. 9 ideas are preserved after the filtering and reconstruction. These ideas are then merged with the idea memory.

- (0) Use diverse ensembles by clustering models based on their error patterns and combining outputs from differently preprocessed inputs (e.g., raw, background-removed, edge maps, thresholded) to capture varied noise characteristics.
- (1) Develop a sliding-window, patch-based model that takes an input region and predicts multiple denoised and super-resolved pixels simultaneously for efficient document enhancement.
- (2) Implement a Waifu2x-inspired deep convolutional network with progressively increasing filter counts and LeakyReLU activations, initialized using He normalization for robust convergence in denoising tasks.
- (3) Augment the training set with simulated 3D deformations, lighting variations, and shadows on text to better match real-world scanning artifacts.
- (4) Identify and compensate for systematic artifacts in the "clean" training targets (e.g., single-pixel halos) by modeling them as noise or adjusting ground-truth labels during training.
- (5) Build a wavelet-domain dual-branch U-Net: decompose inputs with 2D DWT into approximation and detail bands, encode separately, decode and fuse via learned 1\*1 convolutions, integrate CBAM attention modules, and train end-to-end with a composite loss combining pixel RMSE, wavelet-band RMSE, and edge loss, optimized using AdamW with a cosine-annealing LR schedule.
- (6) Apply a GAN-based restoration framework: use a ResNet-based generator and 70\*70 PatchGAN discriminator, train with a combination of L1 pixel loss, adversarial loss, stroke-consistency loss (via a frozen stroke-feature CNN), and perceptual OCR-feature loss, incorporating R1 gradient penalty and spectral normalization.
- (7) Leverage coupled dictionary learning and non-local aggregation: learn noisy and clean dictionaries simultaneously via coupled K-SVD, reconstruct patches using OMP, enhance self-similarity with block-matching, and fuse reconstructed patches with non-local weighting.
- (8) Implement blind-spot test-time adaptation: randomly mask a small percentage of pixels per batch, train a lightweight CNN with skip connections on the single test image using masked L2 loss and augmentations, fine-tune per image for a few hundred steps, and optionally ensemble multiple initializations for variance reduction.

Based on the ideas received from the Idea Proposer and previous reports, the Coordinator then compiles 2 solution drafts.

## Pipeline 1 (Baseline CNN - U-Net with L1 loss and simple augmentations)

-----  
Overview

- A lightweight U-Net trained on 256\*256 patches of noisy/clean document pairs.
- Single-branch encoder-decoder with skip connections, ReLU activations, batch norm.
- Loss: L1 pixel-wise loss (less sensitive to outliers than MSE), optional total variation regularization.
- Optimizer: Adam; train on 1 A6000 within 1 hr.

## Data Preparation

1. Read all noisy (input) and clean (target) train images, normalize intensities to [0,1].
2. Extract random 256\*256 patches (stride = 128) with matching noisy/clean pairs.
3. Data augmentation: random horizontal/vertical flips, +-90 degree rotations.
4. Create PyTorch DataLoader with batch\_size=16 (fits 48 GB) for ~100 k patches.

## Network Architecture (PyTorch pseudocode)

```

'''
class UNet(nn.Module):
    def __init__(self):
        super().__init__()
        # Encoder
        self.enc1 = DoubleConv(1, 64)
        self.enc2 = Down(64,128)
        self.enc3 = Down(128,256)
        self.enc4 = Down(256,512)
        # Bottleneck
        self.bottleneck = Down(512,512)
        # Decoder
        self.up4 = Up(1024,256)
        self.up3 = Up(512,128)
        self.up2 = Up(256,64)
        self.up1 = Up(128,64)
        self.final = nn.Conv2d(64,1,kernel_size=1)
    def forward(self,x):
        e1=self.enc1(x)
        e2=self.enc2(e1)
        e3=self.enc3(e2)
        e4=self.enc4(e3)
        b = self.bottleneck(e4)
        d4=self.up4(b,e4)
        d3=self.up3(d4,e3)
        d2=self.up2(d3,e2)
        d1=self.up1(d2,e1)
        return torch.sigmoid(self.final(d1))
'''

```

## Helper modules:

- DoubleConv = (Conv2d -> BatchNorm2d -> ReLU) \*2
- Down = (MaxPool2d -> DoubleConv)
- Up = (ConvTranspose2d for upsampling -> concatenate skip -> DoubleConv)

## Training

- Loss = L1Loss(output, target) + lambda\*TV(output) (lambda=1e-5 for smoothness).
- Optimizer = Adam(lr=1e-3, weight\_decay=1e-5).
- LR schedule: ReduceLROnPlateau(monitor=val\_loss, factor=0.5, patience=5).
- Train for up to 50 epochs; early-stop if val\_loss stagnates.
- Validation: hold out 10% patches to monitor RMSE.

## Inference

- For each test image (e.g., 540\*258), slide 256\*256 window with stride=128, predict, and average overlapping outputs.
- Threshold nothing; output raw [0,1] floats per pixel.

## Compute Budget

- ~100 k patches, batch 16, ~6 k steps per epoch. On A6000: ~2-3 min/epoch => 50 epochs ~ 2 hr ; with early stopping < 1 hr.

## Pipeline 2 (Advanced Wavelet U-Net with CBAM and Composite Loss)

-----  
Overview

- Dual-branch U-Net operating in wavelet domain (Haar DWT) to explicitly denoise tonal and textural components.
- CBAM (Convolutional Block Attention Modules) to adaptively weigh spatial/channel features.
- Loss = alpha\*L1\_pixel + beta\*L2\_wavelet + gamma\*EdgeLoss.
- Optimizer = AdamW + CosineAnnealingLR.

## Data Preparation

- Same as Pipeline 1 (256\*256 patches + augmentations).
- On-the-fly DWT: for each noisy patch, compute one-level Haar DWT -> yields approximation (A) and details (H,V,D).

## Network Architecture

```
(implemented in PyTorch)
'''
class WaveletUNet(nn.Module):
    def __init__(self):
        super().__init__()
        # Shared CBAM-Res blocks for Approx and Detail branches
        self.encA1 = CBAMResBlock(1, 64)
        self.encD1 = CBAMResBlock(3, 64)
        self.pool = nn.MaxPool2d(2)
        self.encA2 = CBAMResBlock(64, 128)
        self.encD2 = CBAMResBlock(64, 128)
        # Bottleneck
        self.bottleneck = CBAMResBlock(256, 256)
        # Decoder
        self.up2 = UpRes(256, 128)
        self.up1 = UpRes(128, 64)
        self.final = nn.Conv2d(64, 4, kernel_size=1)
    def forward(self, x):
        # x shape: [B,1,H,W]
        A, (H,V,D) = haar_dwt(x) # PyWavelets or custom conv
        d0 = torch.cat([self.encA1(A), self.encD1(torch.cat([H,V,D],dim=1))],dim=1)
        p1 = self.pool(d0)
        d1 = torch.cat([self.encA2(p1[:, :128]), self.encD2(p1[:, 128:])],dim=1)
        b = self.bottleneck(self.pool(d1))
        u2 = self.up2(b,d1)
        u1 = self.up1(u2,d0)
        out = self.final(u1) # [B,4,H,W]
        # Reconstruct denoised x via inverse DWT
        A_hat, H_hat,V_hat,D_hat = out[:,0:1], out[:,1:2], out[:,2:3], out[:,3:4]
        return ihaar_dwt((A_hat, (H_hat,V_hat,D_hat)))
'''

Key building blocks:
- CBAMResBlock: residual block with Conv-BN-ReLU->Conv-BN, plus CBAM (channel & spatial attention after second Conv).
- UpRes: ConvTranspose2d upsample->concatenate skip->CBAMResBlock.

Loss
- L1_pixel = L1(output, target).
- L2_wavelet = L2(DWT(output) - DWT(target)).
- EdgeLoss = L1(Sobel(output), Sobel(target)).
- TotalLoss = alpha*L1_pixel + beta*L2_wavelet + gamma*EdgeLoss (alpha=1, beta=0.5, gamma=0.2)

Training
- Optimizer: AdamW(lr=1e-3, weight_decay=1e-4).
- Scheduler: CosineAnnealingLR(T_max=50).
- Batch size=8 (higher memory due to dual branches).
- Epochs=50, early-stop by composite loss on val set.

Inference
- Same sliding-window approach as Pipeline 1.

Compute Budget
- CBAM and wavelet layers add ~1.5* compute but within A6000 48 GB: patch batch=8 yields ~250 steps/epoch, so 50 epochs ~2 hr. Use early-stop or T_max=30 to finish within 1 hr.

References
- CBAM: Woo et al., "CBAM: Convolutional Block Attention Module" (ECCV 2018).
- Haar DWT: PyWavelets or custom conv filters.
- Edge loss: Sobel via fixed conv kernels.

Expected Benefits
- Explicit noise suppression in high-frequency bands.
- Attention modules focus on text strokes and edge restoration.
- Composite loss balances global structure and fine details.
```

In our experiment, 2 parallel Coding Agents are invoked to implement the solution drafts respectively. Each instance has a quota of 20 steps, 3 hours in total and 1 hour per execution. An LLM is instructed to monitor the execution process and terminate failed runs.

The best code snippet generated in the first iteration is:

```
1 import os, glob, random, math
2 from PIL import Image
3 import torch
4 import torch.nn as nn
5 import torch.nn.functional as F
6 from torch.utils.data import Dataset, DataLoader
```

```

7  from torchvision import transforms
8
9
10 # -- 1) Haar DWT / inverse DWT --
11 class HaarDWT(nn.Module):
12     def __init__(self):
13         super().__init__()
14         wt = torch.zeros(4, 1, 2, 2)
15         wt[0, 0, :, :] = 0.5
16         wt[1, 0, 0, 0], wt[1, 0, 0, 1], wt[1, 0, 1, 0], wt[1, 0, 1, 1] = (
17             0.5,
18             -0.5,
19             0.5,
20             -0.5,
21         )
22         wt[2, 0, 0, 0], wt[2, 0, 0, 1], wt[2, 0, 1, 0], wt[2, 0, 1, 1] = (
23             0.5,
24             0.5,
25             -0.5,
26             -0.5,
27         )
28         wt[3, 0, 0, 0], wt[3, 0, 0, 1], wt[3, 0, 1, 0], wt[3, 0, 1, 1] = (
29             0.5,
30             -0.5,
31             -0.5,
32             0.5,
33         )
34         self.register_buffer("weight", wt)
35
36     def forward(self, x):
37         return F.conv2d(x, self.weight, stride=2)
38
39
40 class HaarIDWT(nn.Module):
41     def __init__(self):
42         super().__init__()
43         wt = HaarDWT().weight.clone()
44         self.conv = nn.ConvTranspose2d(4, 1, 2, stride=2, bias=False)
45         self.conv.weight.data.copy_(wt)
46         self.conv.weight.requires_grad_(False)
47
48     def forward(self, coeffs):
49         return self.conv(coeffs)
50
51
52 # -- 2) Sobel edge for EdgeLoss --
53 class Sobel(nn.Module):
54     def __init__(self):
55         super().__init__()
56         kx = torch.tensor(
57             [[1, 0, -1], [2, 0, -2], [1, 0, -1]], dtype=torch.float32
58         ).view(1, 1, 3, 3)
59         ky = torch.tensor(
60             [[1, 2, 1], [0, 0, 0], [-1, -2, -1]], dtype=torch.float32
61         ).view(1, 1, 3, 3)
62         self.register_buffer("wx", kx)
63         self.register_buffer("wy", ky)
64
65     def forward(self, x):
66         gx = F.conv2d(x, self.wx, padding=1)
67         gy = F.conv2d(x, self.wy, padding=1)
68         return torch.sqrt(gx * gx + gy * gy + 1e-6)
69
70
71 # -- 3) CBAM, ResBlock, UpRes, WaveletUNet --

```

```

72 class CBAM(nn.Module):
73     def __init__(self, c, r=16, k=7):
74         super().__init__()
75         self.mlp = nn.Sequential(
76             nn.Linear(c, c // r, bias=False),
77             nn.ReLU(inplace=True),
78             nn.Linear(c // r, c, bias=False),
79         )
80         self.spatial = nn.Conv2d(2, 1, kernel_size=k, padding=k // 2, bias=
            False)
81
82     def forward(self, x):
83         b, c, h, w = x.shape
84         avg = F.adaptive_avg_pool2d(x, 1).view(b, c)
85         mx = F.adaptive_max_pool2d(x, 1).view(b, c)
86         ca = torch.sigmoid(self.mlp(avg) + self.mlp(mx)).view(b, c, 1, 1)
87         x2 = x * ca
88         avgc = x2.mean(1, True)
89         maxc, _ = x2.max(1, True)
90         sa = torch.sigmoid(self.spatial(torch.cat([avgc, maxc], 1)))
91         return x2 * sa
92
93
94 class CBAMResBlock(nn.Module):
95     def __init__(self, inp, outp):
96         super().__init__()
97         self.conv1 = nn.Conv2d(inp, outp, 3, padding=1, bias=False)
98         self.bn1 = nn.BatchNorm2d(outp)
99         self.conv2 = nn.Conv2d(outp, outp, 3, padding=1, bias=False)
100        self.bn2 = nn.BatchNorm2d(outp)
101        self.cbam = CBAM(outp)
102        self.skip = (
103            nn.Conv2d(inp, outp, 1, bias=False) if inp != outp else nn.
                Identity()
104        )
105        self.relu = nn.ReLU(inplace=True)
106
107    def forward(self, x):
108        idt = self.skip(x)
109        out = self.relu(self.bn1(self.conv1(x)))
110        out = self.bn2(self.conv2(out))
111        out = self.cbam(out) + idt
112        return self.relu(out)
113
114
115 class UpRes(nn.Module):
116     def __init__(self, ic, sc, oc):
117         super().__init__()
118         self.up = nn.ConvTranspose2d(ic, oc, 2, stride=2)
119         self.block = CBAMResBlock(oc + sc, oc)
120
121    def forward(self, x, skip):
122        x = self.up(x)
123        if x.shape[-2:] != skip.shape[-2:]:
124            x = F.interpolate(
125                x, size=skip.shape[-2:], mode="bilinear", align_corners=False
126            )
127        return self.block(torch.cat([x, skip], 1))
128
129
130 class WaveletUNet(nn.Module):
131     def __init__(self):
132         super().__init__()
133         self.dwt = HaarDWT()
134         self.idwt = HaarIDWT()

```

```

135     self.eA1 = CBAMResBlock(1, 64)
136     self.eD1 = CBAMResBlock(3, 64)
137     self.pool = nn.MaxPool2d(2)
138     self.eA2 = CBAMResBlock(64, 128)
139     self.eD2 = CBAMResBlock(64, 128)
140     self.b = CBAMResBlock(256, 256)
141     self.u2 = UpRes(256, 256, 128)
142     self.u1 = UpRes(128, 128, 64)
143     self.final = nn.Conv2d(64, 4, 1)
144
145     def forward(self, x):
146         A, H, V, D = self.dwt(x).chunk(4, 1)
147         a1 = self.eA1(A)
148         d1 = self.eD1(torch.cat([H, V, D], 1))
149         d0 = torch.cat([a1, d1], 1)
150         p1 = self.pool(d0)
151         pA, pD = p1[:, :64], p1[:, 64:]
152         a2 = self.eA2(pA)
153         d2 = self.eD2(pD)
154         d1b = torch.cat([a2, d2], 1)
155         b = self.b(self.pool(d1b))
156         u2 = self.u2(b, d1b)
157         u1 = self.u1(u2, d0)
158         out = self.final(u1)
159         return self.idwt(out)
160
161
162 # -- 4) OCRDataset for full training --
163 class OCRDataset(Dataset):
164     def __init__(self, noisy, clean, pp, ps, mode):
165         self.noisy = noisy
166         self.clean = clean
167         self.pp = pp
168         self.ps = ps
169         self.mode = mode
170         self.toT = transforms.ToTensor()
171
172     def __len__(self):
173         return len(self.noisy) * self.pp
174
175     def __getitem__(self, idx):
176         ii = idx // self.pp
177         n = Image.open(self.noisy[ii]).convert("L")
178         c = Image.open(self.clean[ii]).convert("L")
179         tn, tc = self.toT(n), self.toT(c)
180         H, W = tn.shape[-2], tn.shape[-1]
181         y = random.randint(0, H - self.ps)
182         x = random.randint(0, W - self.ps)
183         tn = tn[:, y : y + self.ps, x : x + self.ps]
184         tc = tc[:, y : y + self.ps, x : x + self.ps]
185         if self.mode == "train":
186             if random.random() < 0.5:
187                 tn, tc = torch.flip(tn, [-1]), torch.flip(tc, [-1])
188             if random.random() < 0.5:
189                 tn, tc = torch.flip(tn, [-2]), torch.flip(tc, [-2])
190             k = random.randint(0, 3)
191             if k > 0:
192                 tn, tc = torch.rot90(tn, k, [1, 2]), torch.rot90(tc, k, [1,
193                     2])
194         return tn, tc
195
196 # -- 5) Prepare train/val split --
197 all_no = sorted(glob.glob("./input/train/*.png"))
198 all_cl = sorted(glob.glob("./input/train_cleaned/*.png"))

```

```

199 idxs = list(range(len(all_no)))
200 random.seed(42)
201 random.shuffle(idxs)
202 split = int(0.9 * len(idxs))
203 tr_idx, va_idx = idxs[:split], idxs[split:]
204 noisy_tr = [all_no[i] for i in tr_idx]
205 clean_tr = [all_cl[i] for i in tr_idx]
206 noisy_va = [all_no[i] for i in va_idx]
207 clean_va = [all_cl[i] for i in va_idx]
208
209 # -- 6) DataLoaders --
210 train_ds = OCRDataset(noisy_tr, clean_tr, pp=25, ps=256, mode="train")
211 val_ds = OCRDataset(noisy_va, clean_va, pp=1, ps=256, mode="val")
212 train_loader = DataLoader(
213     train_ds, batch_size=8, shuffle=True, num_workers=4, pin_memory=True
214 )
215 val_loader = DataLoader(
216     val_ds, batch_size=1, shuffle=False, num_workers=2, pin_memory=True
217 )
218
219 # -- 7) Model, optimizer, scheduler, loss w/ tuned weights --
220 device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
221 model = WaveletUNet().to(device)
222 dwt = HaarDWT().to(device)
223 sobel = Sobel().to(device)
224 opt = torch.optim.AdamW(model.parameters(), lr=1e-3, weight_decay=1e-4)
225 sched = torch.optim.lr_scheduler.CosineAnnealingLR(opt, T_max=30)
226
227 # Tuned weights
228 alpha = 0.769634
229 beta = 0.430968
230 gamma = 0.250750
231
232
233 def composite_loss(o, t):
234     l1 = F.l1_loss(o, t)
235     l2 = F.mse_loss(dwt(o), dwt(t))
236     e1 = F.l1_loss(sobel(o), sobel(t))
237     return alpha * l1 + beta * l2 + gamma * e1
238
239
240 # -- 8) Train + validate --
241 best_rmse = 1e9
242 patience = 5
243 wait = 0
244 for epoch in range(1, 31):
245     model.train()
246     tloss = 0.0
247     for xb, yb in train_loader:
248         xb, yb = xb.to(device), yb.to(device)
249         pred = model(xb)
250         loss = composite_loss(pred, yb)
251         opt.zero_grad()
252         loss.backward()
253         opt.step()
254         tloss += loss.item()
255     sched.step()
256
257     # sliding-window validation
258     model.eval()
259     rmse_sum = 0.0
260     stride, ps = 128, 256
261     with torch.no_grad():
262         for nf, cf in zip(noisy_va, clean_va):
263             imn = Image.open(nf).convert("L")

```

```

264         imc = Image.open(cf).convert("L")
265         tn = transforms.ToTensor()(imn).unsqueeze(0).to(device)
266         tc = transforms.ToTensor()(imc).unsqueeze(0).to(device)
267         _, _, H, W = tn.shape
268         acc = torch.zeros_like(tn)
269         cnt = torch.zeros_like(tn)
270         xs = list(range(0, W - ps + 1, stride)) + [W - ps]
271         ys = list(range(0, H - ps + 1, stride)) + [H - ps]
272         for x in xs:
273             for y in ys:
274                 p = tn[:, :, y : y + ps, x : x + ps]
275                 out = model(p)
276                 acc[:, :, y : y + ps, x : x + ps] += out
277                 cnt[:, :, y : y + ps, x : x + ps] += 1
278         rec = acc / cnt
279         mse = F.mse_loss(rec, tc).item()
280         rmse_sum += math.sqrt(mse)
281     val_rmse = rmse_sum / len(noisy_va)
282     print(
283         f"Epoch {epoch}: train_loss={tloss/len(train_loader):.4f}, val_RMSE
          ={val_rmse:.6f}"
284     )
285
286     if val_rmse < best_rmse:
287         best_rmse = val_rmse
288         wait = 0
289         torch.save(model.state_dict(), "./working1/best.pth")
290     else:
291         wait += 1
292         if wait >= patience:
293             print("Early stopping.")
294             break
295
296     print("Best validation RMSE:", best_rmse)
297
298     # -- 9) Inference & submission --
299     model.load_state_dict(torch.load("./working1/best.pth"))
300     model.eval()
301     test_files = sorted(glob.glob("./input/test/*.png"))
302     with open("./working1/submission.csv", "w") as fout:
303         fout.write("id,value\n")
304         for tf in test_files:
305             im = Image.open(tf).convert("L")
306             t = transforms.ToTensor()(im).unsqueeze(0).to(device)
307             _, _, H, W = t.shape
308             acc = torch.zeros_like(t)
309             cnt = torch.zeros_like(t)
310             xs = list(range(0, W - ps + 1, stride)) + [W - ps]
311             ys = list(range(0, H - ps + 1, stride)) + [H - ps]
312             with torch.no_grad():
313                 for x in xs:
314                     for y in ys:
315                         p = t[:, :, y : y + ps, x : x + ps]
316                         out = model(p)
317                         acc[:, :, y : y + ps, x : x + ps] += out
318                         cnt[:, :, y : y + ps, x : x + ps] += 1
319             rec = (acc / cnt).clamp(0, 1).cpu().numpy()[0, 0]
320             img_id = os.path.splitext(os.path.basename(tf))[0]
321             for r in range(H):
322                 for c in range(W):
323                     fout.write(f"{img_id}_{r+1}_{c+1},{rec[r,c]:.6f}\n")
324
325     print("Submission written to ./working1/submission.csv")

```

The Coordinator submits the scripts generated by Coding Agents and their workspace to the community. Then, it proceeds to the second iteration. The report generated by the Analyzer for the second Coding Agent is:

Pipeline:

Our final pipeline is an Advanced Wavelet U-Net with CBAM attention modules, Composite Loss, and sliding-window inference. Specifically:

1. Data Preparation
  - Read all 112 noisy/clean train pairs, split 90/10 train/val by file indices (random seed 42).
  - On-the-fly extract 25 random 256\*256 patches per train image each epoch, with random horizontal/vertical flips and 90 degree rotations.
  - Validation uses a single full-image sliding-window pass (256 patches with 50% overlap) on the 10% hold-out.
2. Model Architecture
  - Haar DWT and inverse DWT implemented as fixed convolutional filters (LL, LH, HL, HH bands)
  - Dual-branch encoder: separate CBAMResBlocks for the approximation (1 channel) and detail (3 channels) coefficients.
  - Two-level downsampling with MaxPool, interleaved CBAMResBlocks, and a 256-channel bottleneck.
  - Decoder with ConvTranspose upsampling and CBAMResBlock skip-connections (UpRes), recombining wavelet bands.
  - Final 1\*1 convolution to 4 coefficient channels and inverse DWT back to image domain.
3. Composite Loss
  - L1(pixels) weighted by alpha=0.769634
  - L2(wavelet coefficients) weighted by beta=0.430968
  - L1(edge Sobel) weighted by gamma=0.250750
4. Training
  - Optimizer: AdamW(lr=1e-3, weight\_decay=1e-4).
  - Scheduler: CosineAnnealingLR(T\_max=30).
  - Batch size 8, 30 epochs, early stopping (patience=5) based on full-image RMSE on the val set.
5. Inference
  - Sliding-window full-image inference with 256\*256 patches, stride=128, averaging overlapped pixels.
  - Generate submission.csv with id=image\_row\_col and float values.
6. Hyperparameter tuning
  - Optuna over (alpha, beta, gamma) on a 20-train/5-val mini-split for 10 trials, each with 2 epochs and 10 patches/image.
  - Best found: alpha=0.769634, beta=0.430968, gamma=0.250750.

Final validation RMSE on 10% hold-out: ~0.012685.

References: CBAM (Woo et al., ECCV 2018), Haar DWT.

Summary:

- Haar DWT:
  - Novelty: 2
  - Rationale: Uses standard 1-level Haar wavelet decomposition.
  - Feasibility: 10
  - Rationale: Straightforward fixed conv implementation in PyTorch.
  - Effectiveness: 6
  - Rationale: Explicit frequency separation aids denoising of high-frequency noise.
  - Efficiency: 9
  - Rationale: Lightweight fixed kernels on GPU.
  - Confidence: 8
  - Rationale: Verified on toy and full runs.
- CBAMResBlock:
  - Novelty: 5
  - Rationale: Incorporates both channel & spatial attention for context-aware features.
  - Feasibility: 8
  - Rationale: Moderate complexity but supported by existing PyTorch modules.
  - Effectiveness: 7
  - Rationale: Improves focus on text strokes, empirically lowers RMSE.
  - Efficiency: 7
  - Rationale: Adds overhead (~1.5\*), but fits within GPU budget.
  - Confidence: 9
  - Rationale: Confirmed across toy and full training.
- UpRes (ConvTranspose + CBAM):
  - Novelty: 3
  - Rationale: Standard upsampling with skip-connections and attention.
  - Feasibility: 9
  - Rationale: Simple extension of ResBlock.

- Effectiveness: 6  
Rationale: Maintains detail in reconstruction.  
Efficiency: 8  
Rationale: Reasonable GPU use.  
Confidence: 8  
Rationale: Working in end-to-end script.
- Wavelet UNet overall:  
Novelty: 7  
Rationale: Dual-branch U-Net in wavelet domain combining DWT, CBAM, skip connections.  
Feasibility: 7  
Rationale: Moderate engineering but fully implemented.  
Effectiveness: 8  
Rationale: Achieved RMSE  $\sim 0.0127$ , strong denoising.  
Efficiency: 7  
Rationale: 25 patches\*8 batch; 30 epochs in  $\sim 20$ min.  
Confidence: 8  
Rationale: Reproducible on A6000.
  - Composite Loss:  
Novelty: 6  
Rationale: Balances pixel, frequency, and edge domains.  
Feasibility: 8  
Rationale: Simple weighted sum.  
Effectiveness: 8  
Rationale: Lower RMSE than L1 or L2 alone.  
Efficiency: 7  
Rationale: Small overhead for extra transforms.  
Confidence: 9  
Rationale: Verified in tuning and full runs.
  - Data Augmentation:  
Novelty: 3  
Rationale: Flips and rotations.  
Feasibility: 10  
Rationale: Trivial to implement.  
Effectiveness: 5  
Rationale: Standard but helpful for invariance.  
Efficiency: 9  
Rationale: CPU-level only.  
Confidence: 9  
Rationale: Common practice.
  - CosineAnnealingLR & EarlyStopping:  
Novelty: 4  
Rationale: Standard learning-rate decay and val-based stop.  
Feasibility: 10  
Rationale: Built-in PyTorch.  
Effectiveness: 6  
Rationale: Helps convergence and prevents overfit.  
Efficiency: 9  
Rationale: Minimal overhead.  
Confidence: 9  
Rationale: Observed smoothed training curves.
  - Sliding-window Inference:  
Novelty: 3  
Rationale: Ensures full-image coverage.  
Feasibility: 10  
Rationale: Straightforward loops.  
Effectiveness: 7  
Rationale: Accurate RMSE measurement, smooth outputs.  
Efficiency: 8  
Rationale: Reasonable inference time ( $\sim 10$  min).  
Confidence: 9  
Rationale: Verified end-to-end.
  - Hyperparameter Tuning (Optuna):  
Novelty: 4  
Rationale: Automated search of loss weights.  
Feasibility: 8  
Rationale: Low-cost mini-training.  
Effectiveness: 7  
Rationale: Found better weights vs. defaults.  
Efficiency: 5  
Rationale: 10 trials \* 2 epochs  $\sim 8$  min.  
Confidence: 7  
Rationale: Verified chosen parameters.

Weaknesses and Suggestions:

1. EMA & TTA Bug: The EMA + 4-way TTA implementation caused RMSE blow-ups, likely due to incorrect accumulation. Before reintroducing, validate TTA on toy splits or isolate EMA without TTA.
  2. Multi-Level Wavelets: Extend to 2-3 levels of DWT to capture coarser scales, with separate branches per level.
  3. Advanced Loss Terms: Incorporate perceptual (VGG) or structural (SSIM) losses to encourage visual fidelity.
  4. Dynamic Loss Weights: Schedule (alpha,beta,gamma) during training (e.g., start with high L1, gradually emphasize wavelet).
  5. Mixed Precision & Gradient Checkpointing: Further reduce memory and speed up with AMP and checkpointing deep layers.
  6. Deeper/Ubiquitous Attention: Explore transformer-style attention (Swin, ViT) in encoder for global context.
  7. Ensemble Models: Train multiple random seeds or architectures (ResUNet, UNet++) and average outputs.
  8. Multi-Scale Inference: Use patches at multiple scales or whole-image passes via down/upscaling for context.
  9. Adaptive Overlap: Use weights at edges of patches to smoothly blend overlaps (Gaussian windows).
  10. Distributed Hyperparameter Search: Scale Optuna across more trials or use BOHB for architecture search.
- Implementing these will likely push RMSE even lower and improve robustness across document noise patterns.  
Full code: ... (omitted)...

Following the brainstorming and idea refinement phases, the current idea memory is presented below. Notably, entries (3), (4), (5), and (7) are newly proposed by the agent, while the remaining ideas have been refined from those in the previous iteration.

- (0) Patch-based convolutional super-resolution denoiser: a sliding-window, patch-based model that predicts multiple denoised and super-resolved pixels per patch. Architecture inspired by Waifu2x with progressively increasing filter counts, LeakyReLU activations, and He initialization for robust convergence.
- (1) Advanced wavelet-domain dual-branch U-Net with CBAM attention and composite loss: decompose inputs via fixed 1-level DWT (LL, LH, HL, HH bands), encode approximation and detail separately with CBAM ResBlocks, decode and fuse via 1\*1 convolutions, and train end-to-end using a weighted sum of pixel L1, wavelet-band L2, and edge L1 losses. Optimized with AdamW and cosine-annealing LR scheduling.
- (2) GAN-based restoration framework: a ResNet-based generator and 70\*70 PatchGAN discriminator trained with combined losses-L1 pixel loss, adversarial loss, stroke-consistency loss (via frozen stroke-feature CNN), and perceptual OCR-feature loss. Includes R1 gradient penalty and spectral normalization for stability.
- (3) Masked autoencoder with vision transformer for denoising: patchify each image into non-overlapping square tokens, randomly mask a high percentage, pretrain a ViT encoder (12 layers, hidden 768, 12 heads) plus light transformer decoder on L2 reconstruction of dirty images, then append an MLP head and fine-tune end-to-end on noisy->clean pairs with L1 pixel + differentiable OCR-confidence loss. Employ random block dropout and color jitter during fine-tuning; at inference use full-image encoding or averaged mask schedules.
- (4) Conditional diffusion-based restoration: define a forward Gaussian-noise diffusion schedule, train a 5-level U-Net conditioned on the dirty image via channel concatenation and FiLM/cross-attention of sinusoidal timestep embeddings. Use the standard DDPM MSE loss with classifier-free guidance, and sample with a deterministic DDIM sampler (~50 steps). Optionally post-process with bilateral or median filtering to remove speckles.
- (5) Learnable spectral gating in the Fourier domain: compute the 2D FFT of the dirty image, split its spectrum into low/mid/high radial bands, apply learnable complex masks per band, and modulate each by gate scalars predicted by a lightweight CNN on the dirty image. Recombine via inverse FFT and train end-to-end with L2 pixel loss plus a spectral-smoothness regularizer on the masks.
- (6) Hypernetwork-modulated U-Net: extract per-image noise statistics (mean, std, skew, kurtosis, histogram bins), feed into an MLP hypernetwork that outputs FiLM scale (gamma) and shift (beta) parameters for selected convolutional feature maps of a base U-shaped CNN. Randomly augment noise levels during training; train end-to-end on noisy->clean with L1 loss and a small regularizer pushing gamma->1, beta->0. At inference compute stats per image, generate FiLM params, and denoise via the modulated U-Net.
- (7) Blind-spot test-time adaptation: for each test image, randomly mask a subset of pixels and fine-tune a lightweight CNN with skip connections on the single image using masked L2 loss and augmentations for a few hundred gradient steps. Optionally ensemble multiple random initializations to reduce variance.
- (8) Multi-model ensemble with diverse preprocessing: cluster trained models by their error patterns and combine their outputs. Apply different preprocessing pipelines (raw, background-removed, edge maps, thresholded) to the input, denoise with clustered sub-ensembles, and fuse predictions for robustness across noise characteristics.
- (9) Enhanced augmentation and target refinement: simulate realistic scanning artifacts by applying 3D text deformations, lighting variations, and shadows to clean images. Identify and compensate for systematic artifacts in the provided 'clean' targets (e.g., single-pixel halos) by either modeling them as noise or adjusting ground-truth labels during training.

And solution drafts generated in this iteration are:

## Pipeline 1: ResNet-34 Encoder U-Net with Multi-Scale Edge &amp; Total-Variation Loss

## Overview:

A robust baseline using a pretrained ResNet-34 backbone as a U-Net encoder fused with a light-weight decoder. Combines L1 loss, Sobel edge loss at multiple scales, and a total-variation regularizer to preserve text strokes while smoothing background noise. Mixed precision training and sliding-window inference ensure the entire pipeline runs in ~45 min on an A6000.

## 1. Data Preparation

- Read all train noisy/clean PNGs, normalize to [0,1].
- Extract on-the-fly 256\*256 patches: random crop + random horizontal/vertical flips + 90 degree rotations.
- 90/10 split by file indices (seed=42). Use batch size 8-16.

## 2. Model Architecture

- Encoder: torchvision.models.resnet34(pretrained=True), first conv modified to 1->64 channels.
- Decoder: four upsampling stages (ConvTranspose2d + Conv2d+BN+ReLU) mirroring ResNet blocks, with skip-connections from encoder layers.
- Final conv 64->1 + Sigmoid.

## 3. Loss Function

Let  $y_{\hat{}}$  and  $y$  be predictions and targets.

- L1Loss( $y_{\hat{}}$ ,  $y$ )
  - Edge loss: L1 between Sobel( $y_{\hat{}}$ ) and Sobel( $y$ ) at both full resolution and half resolution (downsample by 2).
  - TV:  $\lambda \cdot TV(y_{\hat{}})$  where  $TV = \text{mean}(|\nabla_x y_{\hat{}}| + |\nabla_y y_{\hat{}}|)$ .
- Total loss =  $\alpha \cdot L1 + \beta \cdot \text{Edge\_full} + \gamma \cdot \text{Edge\_half} + \delta \cdot TV$ , e.g.  $\alpha=1.0$ ,  $\beta=0.5$ ,  $\gamma=0.25$ ,  $\delta=1e-5$ .

## 4. Optimization

- Optimizer: AdamW(lr=1e-3, weight\_decay=1e-4).
- Scheduler: CosineAnnealingLR(T\_max=25).
- Mixed precision via torch.cuda.amp.
- Early stopping on validation RMSE (patience=5).

## 5. Inference &amp; Submission

- Perform sliding-window inference on each test image with 256\*256 patches, stride=128.
- Average overlapping patches.
- Clamp outputs to [0,1], write submission.csv with id=image\_row\_col.

Compute budget: ~20 min train + ~5 min inference.

## Pipeline 2: Laplacian-Pyramid Multi-Scale Residual U-Net with Pyramid Loss

## Overview:

A novel pyramid-domain network that decomposes images into multi-scale Laplacian bands, denoises each band via shared-weight residual blocks, and merges them back. Multi-level L1 losses focus the model on both coarse structures and fine text details. Efficient and fully end-to-end in PyTorch, training finishes in ~50 min on an A6000.

## 1. Data &amp; Augmentation

- Same data split and patch sampling (256\*256, flips, rotations).

## 2. Laplacian Pyramid Transform (LPT)

- On the fly, for each patch: create 2-level Gaussian pyramid using avg-pooling (scale 1->0.5->0.25), then compute Laplacian bands  $L_0=(I-\text{upsample}(I/2))$ ,  $L_1=(I/2-\text{upsample}(I/4))$ , and a residual low band  $L_2=I/4$ .
- Stack  $[L_0, L_1, L_2]$  as 3 input channels.

## 3. Network

- Encoder-decoder U-Net with 3-channel input and 3-channel output, 4 down/upsampling stages, 64->128->256->512->256->128->64 channel widths.
- Each block: two 3\*3 Conv+BN+ReLU and a residual skip connection.

## 4. Reconstruction

- Output is 3 residual corrections  $R_0, R_1, R_2$  to each band.
- Reconstruct clean patch:  
 $a_0 = L_0 + R_0$ ;  $a_1 = L_1 + R_1$ ;  $a_2 = L_2 + R_2$ ;  
 $I = a_0 + \text{up}(a_1) + \text{up}(\text{up}(a_2))$ .

## 5. Loss Function

- Per-band L1 losses:  $w_0 \cdot L_1(a_0, H_0) + w_1 \cdot L_1(a_1, H_1) + w_2 \cdot L_1(a_2, H_2)$ , where  $H_k$  are ground-truth bands and  $w_0=1.0$ ,  $w_1=0.5$ ,  $w_2=0.25$ .
- Pixel L1:  $\lambda_{\text{pix}} \cdot L_1(I, I_{\text{gt}})$  with  $\lambda_{\text{pix}}=0.1$ .

## 6. Training

- AdamW(lr=5e-4, weight\_decay=1e-5), one-cycle scheduler (max\_lr=5e-4, epochs=30).
- Batch size 8, mixed precision.
- Early stopping on val RMSE (patience=6).

## 7. Inference

- On full test images, run sliding-window with 256\*256 patches, stride=128.
- For each patch, apply pyramid -> model -> reconstruct -> accumulate and average.
- Clamp to [0,1], write submission.csv.

Compute budget: ~25 min training + ~8 min inference.

The best code proposed in the second iteration is:

```

1 import os, random, csv
2 import numpy as np
3 from glob import glob
4 from PIL import Image
5
6 import torch
7 import torch.nn as nn
8 import torch.nn.functional as F
9 from torch.utils.data import Dataset, DataLoader
10 from torchvision import transforms, models as tv_models
11 from torch.cuda.amp import autocast, GradScaler
12
13 # 1) Reproducibility
14 SEED = 42
15 random.seed(SEED)
16 np.random.seed(SEED)
17 torch.manual_seed(SEED)
18 torch.cuda.manual_seed_all(SEED)
19
20 DEVICE = torch.device("cuda" if torch.cuda.is_available() else "cpu")
21
22 # 2) Paths
23 TRAIN_NOISY = "./input/train"
24 TRAIN_CLEAN = "./input/train_cleaned"
25 TEST_DIR = "./input/test"
26 WORK_DIR = "./working0"
27 os.makedirs(WORK_DIR, exist_ok=True)
28
29 # 3) Hyperparameters
30 PATCH_SIZE = 256
31 STRIDE = 128
32 BATCH_SIZE = 12
33 LR, WD = 1e-3, 1e-4
34 MAX_EPOCHS = 50
35 PATIENCE = 10
36 T_MAX = 50 # for LR scheduler
37
38 # 4) Loss-weight constants (from tuning)
39 w1, w2, w3, w4 = 1.0, 0.5, 0.25, 1e-5
40 lambda_aux = 0.4394633936788146
41 lambda_mse = 0.1312037280884873
42 lambda_ssim = 0.031198904067240532
43 lambda_ssim2 = lambda_ssim / 2
44
45
46 # 5) Dataset + augmentations
47 class OCRDataset(Dataset):
48     def __init__(self, noisy_list, clean_list, ps, train):
49         self.noisy, self.clean = noisy_list, clean_list
50         self.ps, self.train = ps, train
51         self.to_tensor = transforms.ToTensor()
52         self.aug = transforms.Compose(
53             [
54                 transforms.RandomChoice(
55                     [
56                         transforms.RandomHorizontalFlip(1.0),

```

```

57         transforms.RandomVerticalFlip(1.0),
58         transforms.RandomRotation(90),
59         transforms.RandomRotation(180),
60         transforms.RandomRotation(270),
61     ]
62     ),
63     transforms.RandomApply([transforms.GaussianBlur(3, (0.1, 2.0)
64     )], p=0.3),
65     transforms.RandomApply([transforms.RandomAdjustSharpness(2.0)
66     ], p=0.3),
67 ]
68 )
69
70 def __len__(self):
71     return len(self.noisy)
72
73 def __getitem__(self, i):
74     n = Image.open(self.noisy[i]).convert("L")
75     c = Image.open(self.clean[i]).convert("L")
76     w, h = n.size
77     # pad
78     if w < self.ps or h < self.ps:
79         pad = (0, 0, max(0, self.ps - w), max(0, self.ps - h))
80         n = transforms.functional.pad(n, pad, fill=255)
81         c = transforms.functional.pad(c, pad, fill=255)
82         w, h = n.size
83     # crop
84     if self.train:
85         x = random.randint(0, w - self.ps)
86         y = random.randint(0, h - self.ps)
87     else:
88         x = (w - self.ps) // 2
89         y = (h - self.ps) // 2
90     n = n.crop((x, y, x + self.ps, y + self.ps))
91     c = c.crop((x, y, x + self.ps, y + self.ps))
92     if self.train and random.random() < 0.5:
93         n = self.aug(n)
94         c = self.aug(c)
95     return self.to_tensor(n), self.to_tensor(c)
96
97 # 6) Prepare train/val split
98 noisy_files = sorted(glob(f"{TRAIN_NOISY}/*.png"))
99 clean_files = [f"{TRAIN_CLEAN}/" + os.path.basename(x) for x in
100     noisy_files]
101 N = len(noisy_files)
102 idx = list(range(N))
103 random.shuffle(idx)
104 ntr = int(0.9 * N)
105 tr_idx, va_idx = idx[:ntr], idx[ntr:]
106 train_noisy = [noisy_files[i] for i in tr_idx]
107 train_clean = [clean_files[i] for i in tr_idx]
108 val_noisy = [noisy_files[i] for i in va_idx]
109 val_clean = [clean_files[i] for i in va_idx]
110
111 train_ds = OCRDataset(train_noisy, train_clean, PATCH_SIZE, train=True)
112 val_ds = OCRDataset(val_noisy, val_clean, PATCH_SIZE, train=False)
113 train_loader = DataLoader(
114     train_ds, batch_size=BATCH_SIZE, shuffle=True, num_workers=4,
115     pin_memory=True
116 )
117 val_loader = DataLoader(
118     val_ds, batch_size=BATCH_SIZE, shuffle=False, num_workers=4,
119     pin_memory=True
120 )

```

```

117
118 # 7) Sobel, TV, SSIM helpers
119 sob_x = (
120     torch.tensor([[1, 0, -1], [2, 0, -2], [1, 0, -1]], dtype=torch.float32
121 )
122     .view(1, 1, 3, 3)
123     .to(DEVICE)
124 )
125 sob_y = sob_x.transpose(2, 3)
126
127 def sobel(x):
128     gx = F.conv2d(x, sob_x, padding=1)
129     gy = F.conv2d(x, sob_y, padding=1)
130     return torch.sqrt(gx * gx + gy * gy + 1e-6)
131
132
133 def total_variation(x):
134     dh = (x[:, :, 1:, :] - x[:, :, :-1, :]).abs().mean()
135     dw = (x[:, :, :, 1:] - x[:, :, :, :-1]).abs().mean()
136     return dh + dw
137
138
139 def ssim_map(a, b, C1=0.01**2, C2=0.03**2):
140     mu_a = F.avg_pool2d(a, 3, 1, 1)
141     mu_b = F.avg_pool2d(b, 3, 1, 1)
142     sa = F.avg_pool2d(a * a, 3, 1, 1) - mu_a * mu_a
143     sb = F.avg_pool2d(b * b, 3, 1, 1) - mu_b * mu_b
144     sab = F.avg_pool2d(a * b, 3, 1, 1) - mu_a * mu_b
145     num = (2 * mu_a * mu_b + C1) * (2 * sab + C2)
146     den = (mu_a * mu_a + mu_b * mu_b + C1) * (sa + sb + C2)
147     return num / (den + 1e-8)
148
149
150 def ssim_loss(a, b):
151     return 1.0 - ssim_map(a, b).mean()
152
153
154 # 8) loss_terms
155 l1_loss = nn.L1Loss()
156 mse_loss = nn.MSELoss()
157
158
159 def loss_terms(pred, target):
160     L1v = l1_loss(pred, target)
161     MSEv = mse_loss(pred, target)
162     Ef = l1_loss(sobel(pred), sobel(target))
163     p2, t2 = F.avg_pool2d(pred, 2), F.avg_pool2d(target, 2)
164     Eh = l1_loss(sobel(p2), sobel(t2))
165     TVv = total_variation(pred)
166     return L1v, MSEv, Ef, Eh, TVv
167
168
169 # 9) Model w/ deep supervision
170 class ResUNetDS(nn.Module):
171     def __init__(self):
172         super().__init__()
173         r34 = tv_models.resnet34(pretrained=True)
174         self.enc0 = nn.Conv2d(1, 64, 7, 2, 3, bias=False)
175         self.enc0.weight.data = r34.conv1.weight.data.mean(dim=1, keepdim=
176             True)
177         self.bn0, self.relu0, self.pool0 = r34.bn1, r34.relu, r34.maxpool
178         self.enc1, self.enc2 = r34.layer1, r34.layer2
179         self.enc3, self.enc4 = r34.layer3, r34.layer4

```

```

180     def up(i, o):
181         return nn.ConvTranspose2d(i, o, 2, 2)
182
183     def cb(i, o):
184         return nn.Sequential(
185             nn.Conv2d(i, o, 3, 1, 1, bias=False),
186             nn.BatchNorm2d(o),
187             nn.ReLU(inplace=True),
188             nn.Conv2d(o, o, 3, 1, 1, bias=False),
189             nn.BatchNorm2d(o),
190             nn.ReLU(inplace=True),
191         )
192
193     self.up4, self.dec4 = up(512, 256), cb(256 + 256, 256)
194     self.up3, self.dec3 = up(256, 128), cb(128 + 128, 128)
195     self.up2, self.dec2 = up(128, 64), cb(64 + 64, 64)
196     self.aux_up, self.aux_out = up(64, 64), nn.Conv2d(64, 1, 1)
197     self.up1, self.dec1 = up(64, 64), cb(64 + 64, 64)
198     self.up0, self.outc = up(64, 64), nn.Conv2d(64, 1, 1)
199     self.sig = nn.Sigmoid()
200
201     def forward(self, x):
202         x0 = self.relu0(self.bn0(self.enc0(x)))
203         x1 = self.pool0(x0)
204         x2 = self.enc1(x1)
205         x3 = self.enc2(x2)
206         x4 = self.enc3(x3)
207         x5 = self.enc4(x4)
208
209         d4 = self.dec4(torch.cat([self.up4(x5), x4], dim=1))
210         d3 = self.dec3(torch.cat([self.up3(d4), x3], dim=1))
211         d2 = self.dec2(torch.cat([self.up2(d3), x2], dim=1))
212         aux = self.sig(self.aux_out(self.aux_up(d2)))
213         d1 = self.dec1(torch.cat([self.up1(d2), x0], dim=1))
214         main = self.sig(self.outc(self.up0(d1)))
215         return main, aux
216
217
218 model = ResUNetDS().to(DEVICE)
219
220 # 10) Optimizer, scheduler, scaler
221 optimizer = torch.optim.AdamW(model.parameters(), lr=LR, weight_decay=WD)
222 scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=
    T_MAX)
223 scaler = GradScaler()
224
225 # 11) Training + snapshot saving
226 best_rmse = float("inf")
227 patience = 0
228 snap_epochs = set([10, 20, 30, 40, 50])
229
230 for epoch in range(1, MAX_EPOCHS + 1):
231     model.train()
232     train_loss = 0.0
233     for noisy_img, clean_img in train_loader:
234         noisy_img, clean_img = noisy_img.to(DEVICE), clean_img.to(DEVICE)
235         optimizer.zero_grad()
236         with autocast():
237             main_pred, aux_pred = model(noisy_img)
238             L1v, MSEv, Ef, Eh, TVv = loss_terms(main_pred, clean_img)
239             s1 = ssim_loss(main_pred, clean_img)
240             p2, t2 = F.avg_pool2d(main_pred, 2), F.avg_pool2d(clean_img, 2)
241             s2 = ssim_loss(p2, t2)
242             main_loss = (
243                 w1 * L1v

```

```

244         + lambda_mse * MSEv
245         + w2 * Ef
246         + w3 * Eh
247         + w4 * TVv
248         + lambda_ssim * s1
249         + lambda_ssim2 * s2
250     )
251     aux_up = F.interpolate(
252         aux_pred,
253         size=clean_img.shape[-2:],
254         mode="bilinear",
255         align_corners=False,
256     )
257     La, Ma, Ea, Eh2, TVa = loss_terms(aux_up, clean_img)
258     sa = ssim_loss(aux_up, clean_img)
259     pa, ca = F.avg_pool2d(aux_up, 2), F.avg_pool2d(clean_img, 2)
260     sa2 = ssim_loss(pa, ca)
261     aux_loss = (
262         w1 * La
263         + lambda_mse * Ma
264         + w2 * Ea
265         + w3 * Eh2
266         + w4 * TVa
267         + lambda_ssim * sa
268         + lambda_ssim2 * sa2
269     )
270     loss = main_loss + lambda_aux * aux_loss
271     scaler.scale(loss).backward()
272     scaler.step(optimizer)
273     scaler.update()
274     train_loss += loss.item()
275     scheduler.step()
276
277     # validation
278     model.eval()
279     se, count = 0.0, 0
280     with torch.no_grad():
281         for noisy_img, clean_img in val_loader:
282             noisy_img, clean_img = noisy_img.to(DEVICE), clean_img.to(DEVICE)
283             with autocast():
284                 pred, _ = model(noisy_img)
285                 se += ((pred - clean_img) ** 2).sum().item()
286                 count += pred.numel()
287     val_rmse = np.sqrt(se / count)
288     print(
289         f"Epoch {epoch}: TrainLoss={train_loss/len(train_loader):.4f},
290         ValRMSE={val_rmse:.6f}"
291     )
292
293     # best + snapshot
294     if val_rmse < best_rmse:
295         best_rmse = val_rmse
296         torch.save(model.state_dict(), os.path.join(WORK_DIR, "best_full.
297            pth"))
298         patience = 0
299     else:
300         patience += 1
301     if epoch in snap_epochs:
302         torch.save(model.state_dict(), os.path.join(WORK_DIR, f"snap_{epoch}
303             .pth"))
304     if patience >= PATIENCE:
305         print("Early stopping.")
306         break

```

```

305 print("Best validation RMSE:", best_rmse)
306
307 # 12) Ensemble load
308 ckpts = ["best_full.pth"] + sorted(
309     [f for f in os.listdir(WORK_DIR) if f.startswith("snap_")],
310     key=lambda x: int(x.split("_")[1].split(".")[0]),
311 )[-2:]
312 ensemble_nets = []
313 for ck in ckpts:
314     net = ResUNetDS().to(DEVICE)
315     net.load_state_dict(torch.load(os.path.join(WORK_DIR, ck)))
316     net.eval()
317     ensemble_nets.append(net)
318
319
320 # 13) Sliding-window ensemble inference
321 def ensemble_infer(img_arr):
322     h, w = img_arr.shape
323     inp = torch.from_numpy(img_arr / 255.0).unsqueeze(0).unsqueeze(0).to(
324         DEVICE)
325     ph = (PATCH_SIZE - h % STRIDE) % STRIDE
326     pw = (PATCH_SIZE - w % STRIDE) % STRIDE
327     inp = F.pad(inp, (0, pw, 0, ph), mode="reflect")
328     _, _, H, W = inp.shape
329     out = torch.zeros_like(inp)
330     wt = torch.zeros_like(inp)
331     for y in range(0, H - PATCH_SIZE + 1, STRIDE):
332         for x in range(0, W - PATCH_SIZE + 1, STRIDE):
333             patch = inp[:, :, y : y + PATCH_SIZE, x : x + PATCH_SIZE]
334             preds = []
335             with torch.no_grad(), autocast():
336                 for net in ensemble_nets:
337                     p, _ = net(patch)
338                     preds.append(p)
339             avg_p = torch.stack(preds, 0).mean(0)
340             out[:, :, y : y + PATCH_SIZE, x : x + PATCH_SIZE] += avg_p
341             wt[:, :, y : y + PATCH_SIZE, x : x + PATCH_SIZE] += 1.0
342     out = out / wt
343     out = out[:, :, :h, :w]
344     return out.detach().cpu().numpy().squeeze()
345
346 # 14) Write submission.csv
347 submission_path = os.path.join(WORK_DIR, "submission.csv")
348 with open(submission_path, "w", newline="") as f:
349     writer = csv.writer(f)
350     writer.writerow(["id", "value"])
351     for tf in sorted(
352         glob(f"{TEST_DIR}/*.png"), key=lambda x: int(os.path.basename(x).
353             split(".")[0])
354     ):
355         img_id = os.path.basename(tf).split(".")[0]
356         img = np.array(Image.open(tf).convert("L"), dtype=np.float32)
357         den = ensemble_infer(img)
358         H, W = den.shape
359         for i in range(H):
360             for j in range(W):
361                 writer.writerow([f"{img_id}_{i+1}_{j+1}", f"{den[i,j]:.6f}"])
362 print("Submission saved to", submission_path)

```