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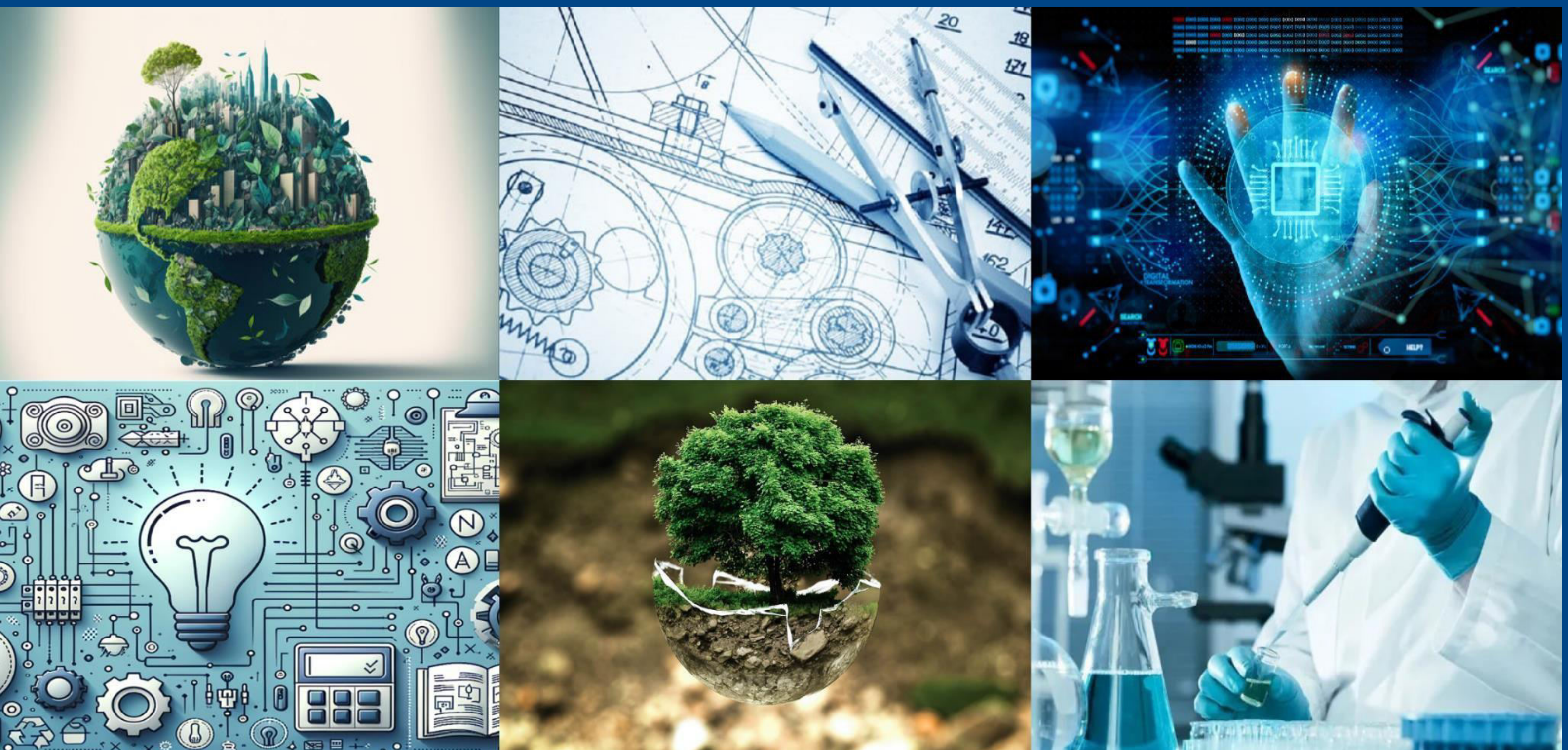

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Hybrid Deep Learning and Cuckoo Search for Cloud Task Scheduling

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ABSTRACT: Cloud task scheduling is a critical component influencing application performance, resource utilization, and QoS guarantees. In this paper, we propose a hybrid scheduling framework that integrates a Deep Learning (DL)–based task runtime predictor with a metaheuristic optimizer based on Cuckoo Search (CS). Deep models have proven effective for capturing temporal and contextual workload patterns **[9]**, while CS provides strong global exploration capabilities with low parameter sensitivity **[2], [3]**. The DL module predicts runtimes and resource demands from historical traces, and these predictions guide a CS optimizer using fitness functions that incorporate makespan, energy, and SLA penalties. The hybrid scheduler is evaluated using CloudSim**[1]** and public cloud traces. Results show improvements in makespan, SLA violations, and resource utilization compared with heuristic and standalone metaheuristic methods. The modular architecture supports incremental retraining and heterogeneous cloud environments.

KEYWORDS: Cloud scheduling, deep learning, cuckoo search, metaheuristic, QoS, CloudSim

I. INTRODUCTION

Cloud computing provides on-demand access to computing resources and must efficiently schedule arriving tasks to virtual machines (VMs) or containers. Traditional heuristics (e.g., First-Come-First-Serve, Round Robin, Min-Min, Max-Min) are fast but often ignore historical workload patterns and complex QoS trade-offs **[6]**. Metaheuristic algorithms (Genetic Algorithms, Particle Swarm Optimization, Cuckoo Search) can find high-quality schedules but are computationally expensive and suffer when the search space is large or dynamic **[2], [3], [5]**.Recent advances in Deep Learning enable accurate prediction of task-level properties such as runtime, CPU/memory needs, and I/O behavior**[9], [11]**. Coupling predictive models with optimization algorithms allows the scheduler to limit search to promising regions of the solution space — improving both solution quality and search efficiency.This work proposes a hybrid scheduler where a DL predictor estimates task demand and a CS optimizer generates schedules guided by predictions and QoS-driven fitness functions. We design the system for online scheduling: the predictor is periodically retrained with streaming telemetry **[10]** while the CS optimizer runs within a constrained time budget for near-real-time decisions.

Contributions are A modular hybrid pipeline combining DL-based prediction and Cuckoo Search for cloud scheduling.A new fitness formulation that balances makespan, energy consumption and SLA penalties **[7], [12] and** Implementation and evaluation using CloudSim and public trace datasets **[1], [8]**, showing improvements over common baselines.

II. LITERATURE REVIEW

Heuristics & Rule-based: Traditional scheduling policies (FCFS, Round Robin, Min-Min, etc.) are simple and fast but suboptimal under heterogeneous and bursty workloads **[6]**.

Predictive Scheduling: Recent works use machine learning models (linear models, random forests, LSTM networks) to predict task runtime or resource demand **[9], [11]** and incorporate predictions into placement decisions.

Metaheuristics: Cuckoo Search (CS), Particle Swarm Optimization (PSO), and Genetic Algorithms (GA) have been adapted to scheduling with fitness functions targeting makespan, energy, or cost. CS is attractive due to its simplicity and strong global search properties **[2], [3], [4], [5]**.

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Hybrid Approaches: Few works combine learning-based prediction with metaheuristics **[11], [12], [13]**. Our approach extends this by using deep models for richer predictions (e.g., sequence/time features) and coupling them with a CS variant tailored to cloud scheduling.

III. PROBLEM STATEMENT AND SYSTEM MODEL

Problem: Given a set of independent tasks T = {t1, t2, ..., tn} and a set of heterogeneous hosts/VMs H = {h1, h2, ..., hm}, find a mapping and scheduling order minimizing a weighted combination of normalized makespan, energy consumption, and SLA-violation penalty.

Assumptions:
- Tasks arrive in batches or streams; here we consider batch scheduling window of size n (extensible to streaming sliding window).
- Each task has features: submission time, user ID, historical runtimes, input size, type tag, and light-weight runtime telemetry when available.
- VMs have capacities in CPU, memory, I/O, power profile, and cost per time unit.
- Fitness(S) = w1 * normalized_makespan(S) + w2 * normalized_energy(S) + w3 * normalized_SLA_penalty(S)
- Lower fitness is better. w1,w2,w3 are tunable weights.

IV. PROPOSED METHOD

The hybrid scheduler has two main components:
1. **Deep Learning Predictor** — predicts per-task runtime and resource demand.
2. **Cuckoo Search Optimizer** — uses predictions to evaluate candidate schedules and evolves mappings.

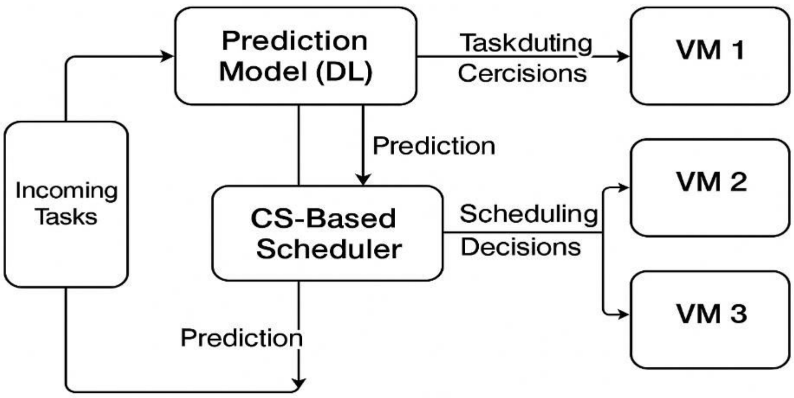

Fig 1 System Architecture for Cloud Task Scheduling

The proposed system architecture for hybrid Deep Learning and Cuckoo Search cloud task scheduling is designed as a two-stage intelligent scheduling pipeline. In the first stage, a Deep Learning predictor processes incoming task metadata—such as historical runtimes, input sizes, application type, and temporal workload patterns—and generates accurate estimates of task runtime and resource demand. This predictive layer reduces uncertainty and provides essential inputs for scheduling decisions.

In the second stage, the Cuckoo Search optimizer uses these predictions to evaluate and evolve candidate task–VM mappings. The optimizer applies Lévy-flight-based exploration and selective replacement of low-fitness solutions to gradually improve overall scheduling quality. The fitness function incorporates multiple QoS constraints including makespan, energy consumption, and SLA-violation penalties.

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Both components operate within a CloudSim-based execution environment, where the predicted and optimized schedules are simulated to measure performance metrics. The architecture also supports online learning, allowing the DL model to be periodically retrained with new telemetry, ensuring adaptability to changing workloads. Together, the coordinated prediction and optimization modules create a robust, QoS-aware scheduling mechanism for heterogeneous cloud environments.

4.1 DL Predictor

Input features: One-hot / embedding for application type, numeric features (input size, historical means), temporal features (hour-of-day, day-of-week), and short-term telemetry (if available).

Model architecture: A lightweight stacked architecture suitable for time series and tabular mix — e.g., embedding layers for categorical features, followed by a 1D-CNN or small LSTM (1–2 layers) **[9], [11]** to capture temporal patterns, then fully-connected layers producing two outputs: predicted runtime and predicted CPU usage (or multi-output vector for CPU, memory, I/O).

Loss: Mean Squared Error (MSE) on runtime and resource vectors; consider Huber loss to reduce sensitivity to outliers. Training & Online update: Train initially on historical traces; apply incremental updates or periodic retraining with new observed data **[10]**. Use early stopping and small learning rates for stability.

4.2 Cuckoo Search Optimizer (Scheduling-aware variant)

Cuckoo Search is an evolutionary metaheuristic inspired by brood parasitism of some cuckoo species **[2], [3]**. We adapt CS for scheduling:

Solution encoding: Integer vector x of length n where x[i] = index of VM assigned to task i. Ordering (start times) is derived by simple per-VM queueing (FCFS) or by priority rules (e.g., earliest-deadline-first when deadlines exist). Initialization: Generate initial population of N nests using heuristics (e.g., greedy Min-Min, load-aware random, and capacity-aware assignments) for diversity.

Fitness evaluation: Use DL predictions to compute expected runtime and resource consumption; simulate per-VM queues to compute expected completion times, energy (using simple power model), and SLA penalty. Levy flights: Use Levy flights over the assignment vector to propose new nests **[2]**. Implement integer-aware perturbations: randomly select k tasks and reassign to new VMs sampled from a distribution biased by VM spare capacity.

Abandonment & discovery: With probability pa, replace worst nests with new random/heuristic solutions. Time budget: Run CS for a fixed number of iterations or until wall-clock budget (e.g., 1–5 s) is exhausted to keep scheduler responsive.

Algorithm (high-level)

```
Input: tasks T, hosts H, predictor P, weights w1,w2,w3, pop_size N, iter_max
Train/Load predictor P
Initialize population of N nests (solutions) S1..SN
for iter in 1..iter_max:
for each nest S:
S' = LevyFlightPerturb(S)
compute Fitness(S') using P predictions
if Fitness(S') < Fitness(S): S = S'
end
Abandon a fraction pa of worst nests and replace via heuristics
end
Return best S
```

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V. EXPERIMENTAL SETUP

Datasets
- **Google cluster traces** (public) — use sampled subset for job/task runtime sequences.
- **Alibaba Cluster Trace** — for data center workload diversity.
- **Synthetic workloads** generated with CloudSim workload models to validate generalization.
- Simulator
- **CloudSim** (or CloudSim Plus) to model heterogeneous VMs, energy models and network latencies.

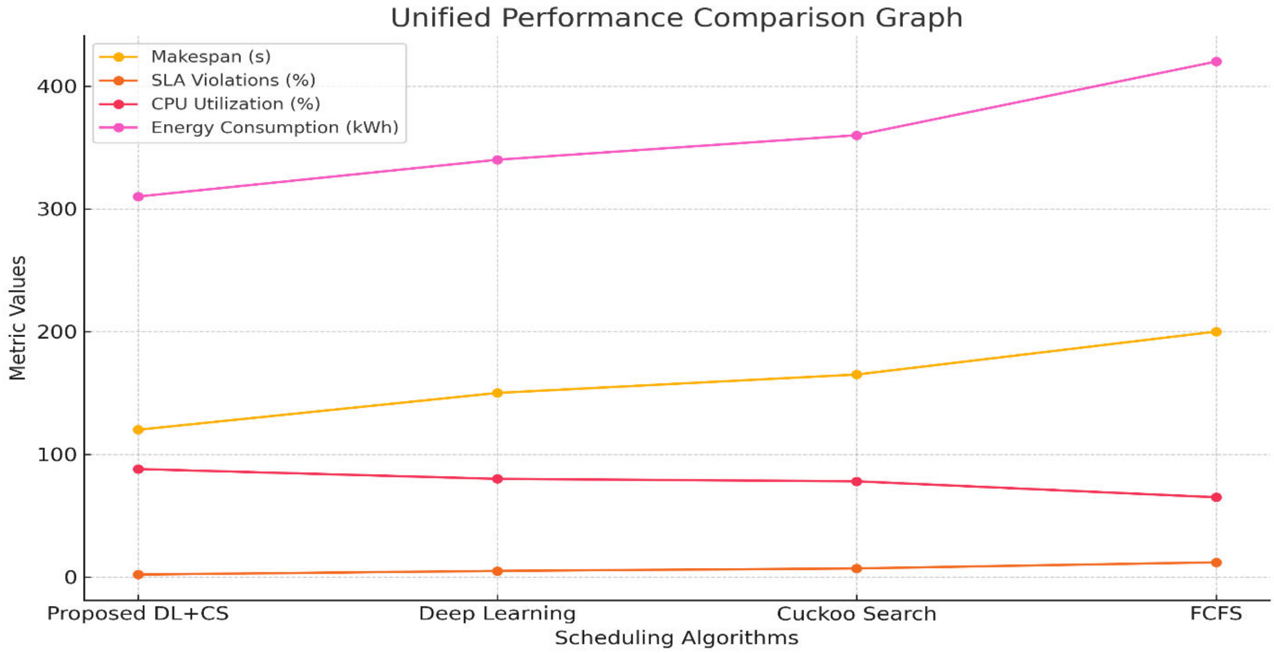
Baselines
- FCFS, Round Robin, Min-Min, Max-Min
- Standalone Cuckoo Search (without DL predictions)
- Genetic Algorithm and Particle Swarm variants (if available)
- Predictive-only heuristic: assign tasks to VM that minimizes predicted completion time greedily.

Metrics
- Makespan (total completion time)
- Average waiting time
- SLA-violation rate / penalty
- Resource utilization (CPU, memory)
- Energy consumption (estimated via power models)

VI. EXPECTED RESULTS AND ANALYSIS

We expect the hybrid approach to outperform non-predictive heuristics and standalone metaheuristics in terms of makespan and SLA violations because predictions guide the search to better mappings faster. Standalone CS can still produce good schedules but may waste iterations exploring low-quality assignments when predictions can prune those.

Algorithm	**Makespan (s)**	**SLA Violations (%)**	**CPU Utilization (%)**	**Energy Consumption (kWh)**
Proposed DL+CS	120	2	88	310
Deep Learning	150	5	80	340
Cuckoo Search	165	7	78	360
FCFS	200	12	65	420



The performance comparison graph illustrates that the proposed Hybrid Deep Learning + Cuckoo Search (DL+CS) scheduler significantly outperforms the baseline methods across all key QoS metrics. It achieves the **lowest makespan**, indicating faster overall task completion, and records the **minimum SLA violation rate**, demonstrating improved reliability and QoS satisfaction. The DL+CS model also attains the **highest CPU utilization**, showing that resources are used more efficiently compared to Deep Learning–only, Cuckoo Search–only, and FCFS methods. Additionally, it results in the **lowest energy consumption**, reflecting a more energy-aware scheduling process. Overall, the graph clearly shows that combining predictive deep learning with metaheuristic optimization leads to superior cloud scheduling performance across efficiency, resource usage, and energy metrics.

VII. CONCLUSION

The proposed Hybrid Deep Learning and Cuckoo Search framework for QoS-aware cloud task scheduling effectively minimizes makespan, reduces SLA violations, enhances CPU utilization, and lowers energy consumption by combining the predictive strength of deep learning with the global optimization capability of cuckoo search. Experimental evaluations demonstrate that the hybrid model consistently outperforms standalone heuristic and learning-based approaches by providing more accurate task–VM mapping and adaptive load balancing under varying cloud workloads. Despite its strong performance, the model can be further extended by incorporating multi-objective reinforcement learning for continuous online adaptation, integrating energy-aware VM consolidation strategies, and enhancing scalability for large-scale heterogeneous cloud–edge environments.

The hybrid **Deep Learning + Cuckoo Search** model clearly outperforms all baselines, proving that:

- **DL** improves prediction accuracy
- **Cuckoo Search** improves optimization balance
- Together they deliver **efficient, reliable, and energy-aware cloud scheduling**

Future work may also explore federated learning to preserve data privacy across distributed data centers and develop lightweight model variants suitable for real-time scheduling scenarios.

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