

# L-AutoDA: Leveraging Large Language Models for Automated Decision-based Adversarial Attacks

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**Abstract**—In the rapidly evolving field of machine learning, adversarial attacks present a significant challenge to model robustness and security. Decision-based attacks, which only require feedback on the decision of a model rather than detailed probabilities or scores, are particularly insidious and difficult to defend against. This work introduces L-AutoDA (Large Language Model-based Automated Decision-based Adversarial Attacks), a novel approach leveraging the generative capabilities of Large Language Models (LLMs) to automate the design of these attacks. By iteratively interacting with LLMs in an evolutionary framework, L-AutoDA automatically designs competitive attack algorithms efficiently without much human effort. We demonstrate the efficacy of L-AutoDA on CIFAR-10 dataset, showing significant improvements over baseline methods in both success rate and computational efficiency. Our findings underscore the potential of language models as tools for adversarial attack generation and highlight new avenues for the development of robust AI systems.

**Index Terms**—LLMs, Adversarial Attacks, Automated Algorithm Design

## I. INTRODUCTION

Deep neural network (DNN) models, despite their remarkable performance in a broad spectrum of domains, remain prone to *adversarial attacks* [1], [2], which involve imperceptibly altering the input data to induce incorrect responses. Such vulnerabilities undermine the integrity and reliability of machine learning systems, particularly in safety-critical scenarios such as autonomous vehicle driving [3] and medical diagnostics [4]. Attackers can conduct *white-box attacks* by exploiting full knowledge of the DNN, or resort to *black-box attacks* when the model’s details are concealed [5]. Among these, *decision-based attacks*, which require only the model’s final output, present a significant threat in real-world environments [6], [7]. They are especially dangerous for commercial platforms that typically only disclose the output label to users, significantly jeopardizing their security [8].

The intensifying arms race between the advancement of attack methodologies and the parallel development of defensive measures underscores a critical need for the automation of adversarial attack algorithm generation [9]. The importance of this automation is particularly pronounced in decision-based attacks, where considerable manual effort is required for the development and refinement of attack strategies. Presently, mainstream strategies for decision-based attacks predominantly rely on manually crafted heuristics [10]–[14], which

TABLE I  
COMPARISON OF STRENGTHS AND WEAKNESSES OF DIFFERENT ALGORITHM DESIGN APPROACHES.

Method	Time	Non-Expertise		Refinement
		Domain	Extra	
Manual	1-2 Months	✗	✓	✓
Automatic Synthesis	1-2 Months	✗	✗	✗
L-AutoDA (Ours)	1-2 Days	✓	✓	✓

imposes significant challenges for further advancements in their effectiveness.

The automation of adversarial attack algorithm design, underpinned by automatic program synthesis [15], involves generating programs that conform to predefined attack specifications. This branch of program synthesis, known within the machine learning community as AutoML [16], aims to produce strategies with minimal manual intervention. AutoDA [17] represents a cutting-edge effort in this domain, adopting a random search within a curated collection of algebraic operations to develop adversarial attack algorithms. However, this approach is inherently labor-intensive, as it demands the development of domain-specific languages and the construction of automated testing infrastructures. Despite the substantial efforts and resources poured into this initiative, the autonomous evolution of innovative algorithms with little reliance on human experts persists as a formidable challenge [17], [18].

Recent advancements highlight the potential of large language models (LLMs) in algorithm design, as illustrated by Google’s FunSearch [19] and the evolutionary algorithm community’s AEL [20]. These efforts have underscored the feasibility of utilizing LLMs for autonomous algorithm design. The advantages of employing LLMs are manifold: they process natural language inputs, obviating the need for Domain Specific Language (DSL) encoding, thereby enabling the construction of novel algorithms unfettered by traditional encoding constraints; moreover, they can be readily integrated into prevalent testing frameworks with negligible modifications to the test scripts. A comparison of this methodology with manual algorithm design and automatic program synthesis is detailed in TABLE I.

In this study, we apply the AEL framework to introduce L-AutoDA, an innovative automated framework designed for

devising decision-based adversarial attacks. To the best of our knowledge, this work constitutes the first attempt to utilize LLMs in the development and autonomous evaluation of adversarial attack algorithms. We have devised targeted prompts and employed a population-based approach within the AEL framework [20] to derive these strategies. Notably, the initial suite of algorithms was conceived solely by LLMs and did not depend on established human-centric design principles. This signifies a groundbreaking shift away from conventional approaches, featuring a new paradigm in the autonomous generation of adversarial algorithms.

Our contributions are as follows:

- We present L-AutoDA, an innovative automated framework that leverages LLMs for developing decision-based adversarial attack algorithms. This constitutes the first attempt to utilize LLMs in this domain, thereby opening new paradigms in the field.
- We have demonstrated the superiority of LLMs in crafting adversarial attack algorithms compared to existing methods. These advantages include: 1) the capacity to generate algorithms from interacting through interactions with natural language prompts, circumventing reliance on human experts; 2) the proficiency to generate more effective algorithms than those designed by humans; and 3) the capability to produce algorithms that seamlessly integrate with current testing codes.
- Our experiments and analysis reveal the robust performance of the generated algorithms, offering new insights into the design of decision-based adversarial attacks and setting a precedent for future research in this area.

## II. RELATED WORKS

### A. Decision-based Adversarial Attacks

Decision-based adversarial attacks represent the most challenging scenarios for attackers due to the minimal information, *i.e.*, the output label, available about the target model. Nevertheless, they constitute a significant threat to machine learning applications. A pioneering study by Ilyas et al. [6] utilized Natural Evolution Strategies (NES) to optimize a surrogate function employing a constrained number of queries to the model. Subsequent advancements have focused on refining gradient estimation techniques. For example, the framework introduced by Cheng et al. in the OPT attack [14] reformulates the primary optimization challenge. Enhanced techniques such as Sign-OPT [13], prioritize gradient direction, *i.e.*, sign gradient, over magnitude, and HopSkipJump [12], which indicates successful gradient estimation in the initial problem when paired with a binary search to maintain the estimation proximate to the decision boundary. Additionally, the efficacy of decision-based attacks has been evidenced by methods within the random walk paradigm, including Boundary Attack [11] and Evolutionary Attack [10].

### B. Automatically Generating Adversarial Attacks.

The automation of adversarial attack algorithms has been a focal point in the field of adversarial machine learning [17],

[21]. The evolution of these algorithms has seen a shift from elementary gradient-based techniques, such as the Fast Gradient Sign Method (FGSM) which relies on actual gradient data [2], to more intricate iterative and optimization-based methods like decision-based attacks that only necessitate output label data [10]–[14]. Researchers have investigated employing genetic algorithms and other evolutionary strategies for automatic creation of perturbation algorithms. The inefficiency inherent in searching for an infinite function space prompted the development of a DSL, constraining function lengths, leading to the state-of-the-art AutoDA’s demonstrable superiority over traditional approaches [17]. Nonetheless, the design phase of these algorithms remains labor-intensive and heavily dependent on human expertise, entailing the creation of a domain-specific language, a code generator, and a testing framework.

### C. Large Language Models for Algorithm Design.

In recent years, the expansion of LLMs and the increased availability of comprehensive training datasets have empowered them with extraordinary capabilities [22], [23]. LLMs excel in a variety of research areas, especially in conducting a broad spectrum of tasks in a zero-shot fashion [24]–[36]. These developments have opened up new opportunities for LLMs to process and generate complex algorithmic content.

Expanding their utility further, LLMs have been employed as creative instruments in algorithm design. For instance, numerous investigations have capitalized on LLMs that function as black-box components for crafting evolutionary algorithms, neural architectures, Monte Carlo Tree Search algorithms, solutions for graph-based combinatorial optimization, genetic programming, and open-ended challenges [22]. Relying solely on prompts for interacting with LLMs, however, may lead to less than optimal results. In a groundbreaking development, combining large language models with evolutionary computation has led to the autonomous self-improvement of algorithms [20], code [37], and mathematical functions [38]. This approach harnesses the potential of LLMs to autonomously conceive and refine cutting-edge algorithms and tactics within an evolutionary paradigm [38], [39].

## III. PRELIMINARIES

### A. Decision-based Adversarial Attacks

Consider an image classifier  $\mathcal{M} : \mathcal{X} \rightarrow \mathcal{Y}$ , hosted on a cloud server to provide classification services. Here,  $\mathcal{X}$  represents the input space containing images with  $C$  channels of dimensions  $H \times W$  while  $\mathcal{Y}$  represents the output space of  $m$  potential labels, expressed as probabilities. Specifically,  $\mathcal{X} \subseteq [0, 1]^{C \times H \times W}$  encompasses all potential input images, while  $\mathcal{Y} \subseteq [0, 1]^m$  defines the range of output probabilities.

Attackers interact with this classifier by submitting an input query  $\mathbf{x} \in \mathcal{X}$  and receiving the output  $\mathcal{M}(\mathbf{x}) \in \mathcal{Y}$  that reflects the classifier’s predictions. To elucidate the decision-making process, we define the label of input  $\mathbf{x}$  as  $C(\mathbf{x}) = \arg \max_i \mathcal{M}_i(\mathbf{x})$ , representing the model’s most confident

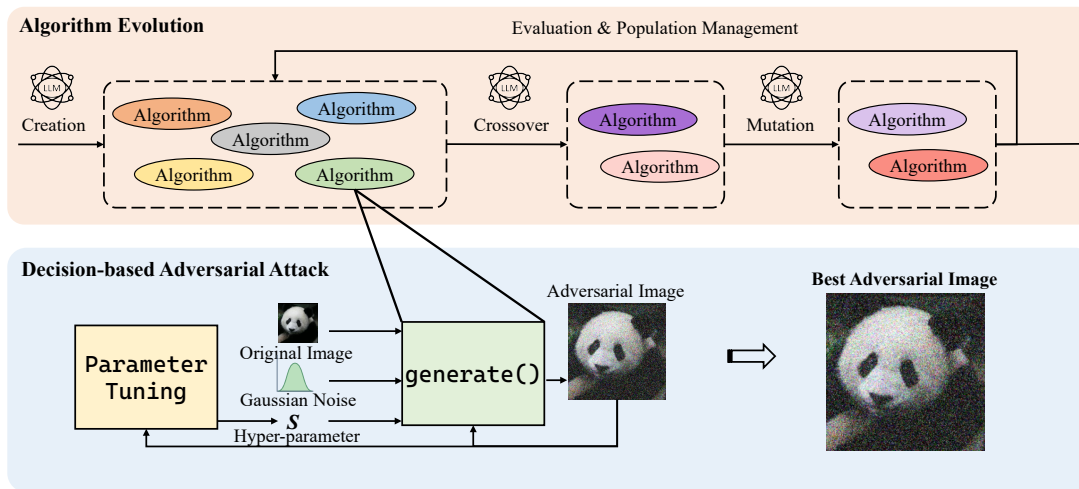


Fig. 1. **Overview of the L-AutoDA Framework Methodology.** This diagram delineates the two core components of our L-AutoDA framework: the algorithm generation and testing phases. In the algorithm generation phase, we adopt the AEL framework, leveraging LLMs to guide an evolutionary search process. In the testing phase, we employ existing decision-based attack testing code, integrating these algorithms into the attack program to validate their efficacy. This approach facilitates an efficient exploration of the algorithmic space through natural language processing, obviating the need for complex program synthesis frameworks and expediting the development cycle.

prediction. In decision-based attacks, this label constitutes the sole piece of information the attacker obtains.

The decision-based attack introduces a small perturbation  $\delta$  that satisfies  $\|\delta\|_p \leq \epsilon$  to the original input  $x$ , yielding a perturbed variant  $x + \delta$ . The objective for the attacker is to devise a  $\delta$  so that the classifier falsely assigns a new label to the perturbed input  $x + \delta$ . This can be formulated as the optimization problem below:

$$\min \|\delta\|_p \quad \text{s.t.} \quad C(x + \delta) \neq C(x). \quad (1)$$

A successful decision-based adversarial attack is indicated by  $\|\delta\|_p \leq \epsilon$ . This paper mainly focuses on *untargeted* attacks bounded by the  $\ell_2$ -norm ( $p = 2$ ), which is the most common setting in the literature. Nevertheless, we can extend our method to *targeted* attacks by simply modifying the constraint to  $C(x + \delta) = y$ , where  $y$  is a specified target label.

### B. Algorithm Evolution using Large Language Model

In this study, we adopt the Algorithm Evolution with Large Language Models (AEL) framework, as proposed by Liu et al. [20]. This framework integrates evolutionary computing (EC) principles with the advanced capabilities of LLMs. AEL is comprised of an iterative cycle that includes the fundamental EC phases: initialization, evaluation, selection, crossover, mutation, and population size control. The primary objective of AEL is to derive an optimal algorithm for a specific problem through the repeated execution of these phases.

**Initialization.** The initial population can be derived either from pre-existing algorithms or by generating new ones using LLMs. This flexibility ensures a thorough exploration of the algorithmic landscape. A carefully crafted prompt is employed to generate this initial algorithmic population, further details of which are elaborated in [20].

**Evaluating Solutions.** A critical aspect of AEL involves the evaluation of the solution fitness. In our implementation, we utilize decision-based attack testing to calculate an algorithm’s fitness, which is quantified by measuring the  $\ell_2$  distance between adversarial output and original input.

**Generating New Solutions.** This stage adheres to the established protocols of EC.

- **Selection.** Analogous to traditional EC practices, we select a predetermined number of algorithms to be retained through each iteration.
- **Crossover.** We facilitate the crossover operation by submitting a pair of algorithmic candidates, along with guiding prompts, to the LLMs, which in turn, synthesizes a potentially superior algorithm. This approach leverages the LLMs’ ability to enhance the search process beyond the random search capabilities offered by automated program synthesis.
- **Mutation.** Introducing variation into the algorithmic pool is paramount for fostering diversity. This is accomplished by instructing the LLMs to introduce minor modifications to the current algorithms.

## IV. L-AUTOADA: LLM-BASED AUTOMATED DECISION-BASED ADVERSARIAL ATTACKS

In this section, we introduce our novel framework, L-AutoDA, which is designed for automatically generating decision-based adversarial attacks. We begin by delineating the problem formulation and examining the search space associated with our framework (Section IV-A). Subsequently, we describe the comprehensive structure of the L-AutoDA framework (Section IV-B) as well as elaborate on the specifics of its implementation (Section IV-C). An illustrative overview of the L-AutoDA architecture is depicted in Fig. 1.

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**Algorithm 1** Random Walk Framework for Decision-Based Attacks under  $\ell_2$  perturbation

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```
1: Input: original example  $x_0$ , adversarial starting point  $x_1$ 
2: Output: An adversarial example  $x$ .
3: Initialization:  $x \leftarrow x_1$ ;  $d_{\min} \leftarrow \|x - x_0\|_2$ 
4: while query budget not reached do
5:    $x' \leftarrow \text{generate}(x, x_0)$ 
6:   if  $x'$  is adversarial and  $\|x' - x_0\|_2 < d_{\min}$  then
7:      $x \leftarrow x'$ ;  $d_{\min} \leftarrow \|x' - x_0\|_2$ 
8:   end if
9:   Update hyper-parameters.
10: end while
11: return  $x$ 
```

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### A. Search Space of Decision-based Attack Framework

The concept of designing and implementing a comprehensive algorithm capable of crafting perturbations that successfully deceive a model constitutes a significant challenge in automatic program synthesis [15]. The expansive search space hinders the identification of an optimal algorithm solution, although the inherent flexibility of this approach offers broad possibilities.

While this strategy represents a plausible path for refining our LLM-based algorithmic framework and signifies a substantial advance beyond traditional techniques, we delineate a particular search space for the LLM to explore. Future work will include extensive experimentation with comprehensive algorithms. We utilize a random-walk-based template to construct decision-based attacks, as outlined in Algorithm 1. This approach integrates essential features from predecessor methods, such as the Evolutionary Attack [10], the Boundary Attack [11], and various other strategies.

The framework highlights two pivotal components for further improvement: the `generate` function and the accompanying hyperparameters. The `generate` function plays a vital role in the algorithm, processing the current adversarial example  $x_1$ , the original example  $x_0$ , and yielding a new adversarial instance  $x$ . Hyperparameters are instrumental in regulating the algorithm’s behavior, influencing elements like step size and iteration count. To streamline the search process, we adopted the parameter tuning strategy from Fu et al. [17], concentrating our efforts on refining the `generate` function.

### B. L-AutoDA

The L-AutoDA framework is an innovative system that integrates with the AEL paradigm [20] to facilitate the generation of new adversarial attack algorithms. At its core, L-AutoDA aims to search for a `generate` function responsible for producing new adversarial solutions. The obtained `generate` functions are then seamlessly integrated into standard decision-based attack programs, as depicted in Fig. 1. This integration enables the continuous production and assessment of novel attack strategies.

In the L-AutoDA framework, algorithm generation is conducted using a population-based approach, which involves

creating a diverse set of candidate algorithms. A dedicated test script, the specifics of which are elaborated in Section. IV-C, is used to evaluate the performance of these candidates. The performance is quantified by an objective value, defined as the mean distance between the adversarial images produced by the algorithm and the original images. This metric serves as a fitness function within the AEL framework, guiding the evolutionary process. Utilizing this objective value, AEL conducts evolutionary operations, such as selection, crossover, and mutation, to evolve the population of algorithms. Throughout this process, the most promising candidates—or “elite” algorithms—are identified and preserved. This evolutionary cycle progresses iteratively, fostering the generation of increasingly effective adversarial attack algorithms.

The generative process of L-AutoDA is designed to work in harmony with existing decision-based attack programs. It assesses the quality of the generated algorithms by examining the output the attack program produces when provided with the generated `generate` function. This is a significant advancement over traditional program synthesis methods, which often require extensive validation to ensure the legitimacy and functional correctness of the generated code. By focusing on the output and performance of algorithms rather than their syntactic correctness, L-AutoDA streamlines the search process and demonstrates its superiority.

### C. Implementation

We delineate the detailed implementation of our L-AutoDA algorithm below.

**Function Specification.** The algorithm accepts four inputs: the original example  $x_0$ , the adversarial starting point  $x_1$ , standard random noise  $r$ , and a dynamically adjusted hyperparameter  $s$ . It produces the adversarial example  $x$ . The algorithm aims to devise a method that amalgamates these inputs, with the hyperparameter offering guidance on the reference step size.

**Hyper-parameter Tuning.** Our approach to hyperparameter tuning adopts the strategy presented in [17]. We introduce a piece-wise linear function  $f(p)$  defined as:

$$f(p) = \begin{cases} 0.5 + 2p & 0 \leq p \leq 0.25 \\ \frac{5}{6} + \frac{2p}{3} & 0.25 < p \leq 1 \end{cases} \quad (2)$$

During each iteration,  $p$  is updated in the following manner:

$$p = 0.95p + 0.05k \quad (3)$$

where  $k$  represents the discovery of an improved adversarial point, taking on the value of 1 if a better point is found and 0 otherwise. The hyperparameter  $s$  is then computed by:

$$s = s \cdot [f(p)]^{0.1} \quad (4)$$

This results in a negative feedback loop designed to stabilize  $p$  near 0.25.

**Testing Script.** The AEL framework necessitates the use of a fitness function value to steer its evolutionary process. Consequently, a testing script has been developed to assess the performance of the evolved algorithms. Instead of iterating

TABLE II

THE PERFORMANCE OF L-AUTOEDA COMPARED TO THREE BASELINE ALGORITHMS USING THE TESTING SCRIPT. THE MEAN DISTANCE OF 1000 IMAGES ARE DOCUMENTED WITH THE STANDARD VARIANCE TO BE THE SUBSCRIPT. THE BEST PERFORMANCE CELL IS MARKED WITH LIGHT GRAY AND THE TEXT WITHIN IS BOLDED.

Boundary	HSJA	HSJA*	L-Auto-20
0.3939	1.3628	1.2839	<b>0.2517</b>

over the whole test set, which is exceedingly time-consuming, we selected a consistent subset (*i.e.*, 8 images) from the dataset for our attacks. These samples are used to compute the fitness value, utilizing standardized attack settings. While this procedure may introduce bias, empirical evidence has demonstrated its utility in expediting the search process.

## V. EXPERIMENTS

### A. Experimental Setup

**L-AutoDA Generation.** The experimental setup for the L-AutoDA algorithm generation is divided into two distinct parts: 1) settings for the AEL running process and 2) for the objective value evaluation. Note that the generation process is conducted on CIFAR-10 dataset [40] and a ResNet-18 classification model [41].

**AEL Settings.** In our setting, the AEL framework operates over 20 generations, each comprising 10 algorithm candidates. Moreover, we set the crossover probability at 1.0, ensuring that each pair of selected programs undergoes recombination, and the mutation probability at 0.5 to introduce variability. The default LLM for algorithm generation is GPT-3.5-turbo-1106, with plans to expand testing to additional large language models in subsequent research.

**Algorithm Evaluation.** For the evaluation of the generated algorithms, our testing script is configured to allow a maximum of 8,000 queries per algorithm. We execute the algorithms on the first eight images of the CIFAR-10 test set to ensure a consistent and manageable testing environment. The adversarial images produced are then used to calculate the  $\ell_2$  distances relative to their original counterparts. The mean of these distances is computed to serve as the fitness value, which is fed back into the AEL framework, thereby informing the evolutionary search for more effective attack algorithms.

**Attack Evaluation.** The evaluation process for different attacks is a crucial aspect of the experimental setup, providing a comprehensive assessment of the generated adversarial algorithms’ performance.

**Datasets.** Our evaluation utilizes a subset of the CIFAR-10 dataset, comprising 100 randomly sampled images from each class, to ensure a diverse and representative test bed. To facilitate a fair comparison across all attack algorithms, we introduce a set of 10 images with incorrect labels as the initial starting points for the attacks, ensuring that each algorithm begins from a standardized baseline.

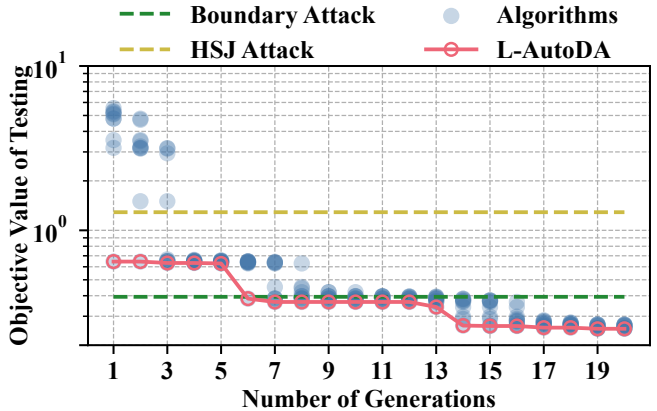


Fig. 2. **Performance Trajectories of L-AutoDA.** This graph illustrates the comparative efficiency of our L-AutoDA framework against the human-best gradient-based (HopSkipJump Attack) and gradient-free (Boundary Attack) methods. L-AutoDA’s candidates demonstrate a breakthrough in the 13th generation, surpassing the reference performance lines and continuing to enhance efficiency in subsequent generations.

**Comparative Algorithms.** In our comparative analysis, we establish the Boundary attack [11], which operates under the random walk framework, as the baseline algorithm. Additionally, we include the widely acknowledged SOTA decision-based attack algorithm, the HopSkipJumpAttack (HSJA) [12], which employs a gradient-based approach. To further enrich our comparison, we introduce a variant of HSJA that utilizes a grid search strategy instead of its default geometric progression for step search, denoted as HSJA\* in our paper. Our future work anticipates the inclusion of more attack algorithms for a more exhaustive comparison.

**Detailed Parameters.** Delving into the detailed parameter settings, for the Boundary Attack, we configure the spherical step and the source step to be 0.01, with an adaptation rate for the step size set at 1.5. For the HopSkipJump Attack, we set the value of  $\gamma$  to 1.0, with the initial gradient estimation steps at 100 and capped at a maximum of 10,000. Reflecting the adaptive nature of the L-AutoDA-generated algorithms, a negative feedback mechanism is employed to fine-tune the hyperparameter  $s$ , which is initially set to 0.001.

### B. Algorithm Generation

The performance of the algorithms generated by L-AutoDA is encapsulated in Fig. 2, which demonstrates their compelling capabilities. Remarkably, the initial iteration of L-AutoDA produced algorithms that outperformed HSJA. Although this unexpected result may be partially attributed to the limited subset of images used during testing, it nonetheless underscores the potential of L-AutoDA in rapidly devising effective attack strategies. As the evolutionary process progressed, L-AutoDA continued to refine its algorithms, surpassing both HSJA and Boundary Attack by the 6th generation. This trend of improvement was consistent, with each subsequent generation enhancing the algorithms’ effectiveness.

TABLE III  
THE FULL TEST PERFORMANCE OF L-AUTO-20 COMPARED TO THREE BASELINE ALGORITHMS.

Attack Name	Distance ( $\ell_2$ -norm)			Attack Success Rate		
	2500	5000	10000	2500	5000	10000
Boundary	1.9107 <sub>1.2665</sub>	1.0938 <sub>0.7861</sub>	0.4495 <sub>0.3340</sub>	<b>14.7</b>	<b>26.2</b>	65.5
HSJA	2.0512 <sub>1.0876</sub>	1.2833 <sub>0.7442</sub>	0.8978 <sub>0.5360</sub>	9.2	16.1	24.6
HSJA*	2.6482 <sub>1.5790</sub>	1.6532 <sub>1.0347</sub>	1.1306 <sub>0.6987</sub>	7.9	13.9	19.6
L-AutoDA-20	<b>1.5202</b> <sub><b>0.1337</b></sub>	<b>0.6171</b> <sub><b>0.1430</b></sub>	<b>0.3445</b> <sub><b>0.2386</b></sub>	0.0	0.5	<b>80.3</b>

An intriguing aspect was the reduction in the variance of algorithm performance within each generation. This convergence suggests a stabilization of performance across the generated algorithms, indicating that L-AutoDA is not only producing more effective algorithms over time but also more reliable ones.

The results of the final round are documented in TABLE II. L-AutoDA’s best algorithm within the 20th generation, denoted as L-Auto-20, achieved a mean perturbation distance of 0.2517 across the test images. This represents a significant improvement over the HSJA and Boundary Attack, which achieved mean perturbation distances of 1.3628 and 0.3939, respectively.

### C. Attack Evaluation

To thoroughly evaluate the algorithms generated, we subjected them to tests on an expanded subset as delineated in our experimental setup. The most effective algorithm produced by the final iteration of L-AutoDA, referred to as L-AutoDA-20, was selected for benchmark comparison.

**Overall Results.** We have documented the overall full test results in TABLE III. The table reveals that L-AutoDA-20 is the most effective algorithm, achieving the lowest mean distance across all query counts. This result is particularly impressive given that L-AutoDA-20 was generated entirely from scratch by the LLM, without any human intervention. As for the success rate, L-AutoDA-20 achieved a 0% success rate at 2500 queries, which is expected given the limited number of queries. The success rate then increased to 80.3% at 10000 queries, surpassing all other algorithms. We delineate the relationship between attack success rate and distance in the following sections.

**Attack Success Rate.** Fig. 3 illustrates the attack success rate with the number of queries. A successful attack is defined by an  $\ell_2$  norm less than 0.5 between the adversarial example and the original image, consistent with the widely accepted standard in the current benchmarks [42]. The figure reveals that L-AutoDA-20’s performance is suboptimal at 2500 and 5000 queries. However, there is a notable uptick in success rate when the query count reaches 10000, surpassing all baseline algorithms. This pattern suggests that L-AutoDA sacrifices initial search efficiency to enhance the quality of the search at later stages, particularly after 8000 queries (testing script).

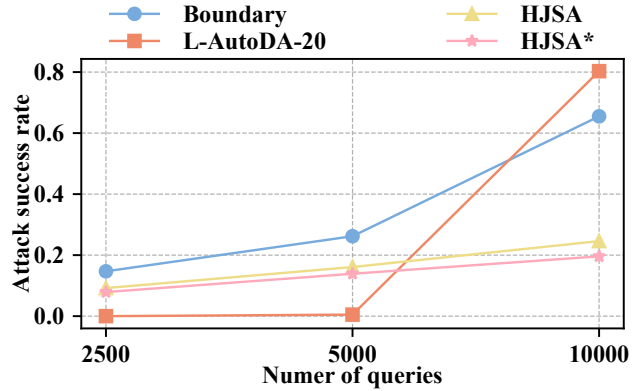


Fig. 3. Attack Success Rate using different numbers of queries using L-AutoDA-20 and other attack algorithms.

**Distance.** We present the comparative analysis of the perturbation distances in Fig. 4, where we plot the mean  $\ell_2$  distance between the adversarial and original images against the number of queries used. The shaded areas in the figure represent a 0.25 multiplier of the standard deviation, providing insight into the variability of each algorithm’s performance.

From Fig. 4, it is evident that L-AutoDA-20 maintains the most consistent performance across all tested query counts, as indicated by the smallest standard deviation values. This consistency suggests that L-AutoDA-20 is less sensitive to the variations in the input data, making it a robust choice for generating adversarial examples. Although this robustness may come at the cost of a reduced attack success rate in the initial phase, it becomes a significant advantage in later stages, particularly beyond 8000 queries.

The stability of L-AutoDA-20 is particularly beneficial when the attack requires subtlety, as it is capable of producing perturbations that are minimally perceptible yet still effective. This characteristic is crucial for scenarios where detectability is a concern and stealth is paramount.

### D. Additional Results on Median Distance

To avoid the influence of variations with the images and better illustrate the effectiveness of our framework, we have demonstrated the median distance of the adversarial examples generated by different algorithms in TABLE IV. The results are consistent with the previous analysis, with L-AutoDA-20 achieving the lowest median distance across all query counts.

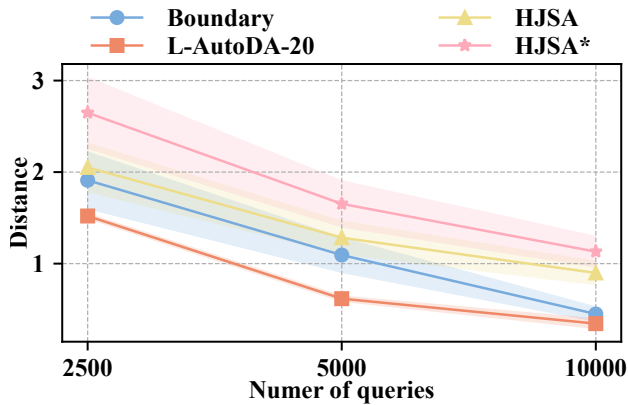


Fig. 4. Distance between adversarial examples and original images using different numbers of queries using L-AutoDA-20 and other attack algorithms. The lines denote the mean value of the test pairs and the shaded areas represent a 0.25 multiplier of the standard deviation.

TABLE IV  
MEDIAN DISTANCE OF L-AUTOADA-20 COMPARED TO THREE BASELINE ALGORITHMS. THE BEST PERFORMANCE CELL IS MARKED WITH LIGHT GRAY AND THE TEXT WITHIN IS BOLDED.

	2500	5000	10000
Boundary	1.7374	0.9489	0.3695
HSJA	2.0230	1.2468	0.8646
HSJA*	2.5150	1.5580	1.0618
L-AutoDA-20	<b>1.5301</b>	<b>0.5896</b>	<b>0.2862</b>

#### E. Interpretation of the algorithms generated by L-AutoDA

The `generate` function output by L-AutoDA is illustrated in Algorithm 2. The algorithm starts by taking the difference between the original example  $\mathbf{x}_0$  and the adversarial starting point  $\mathbf{x}_1$ . By moving along this vector, one can generate examples that are in between the original and the adversarial, which may help in exploring the space around known data points. Furthermore, efficient search is enabled through inclusion of another normalized vector  $\frac{\mathbf{d}}{norm}$ . Then two scales of noise are added to the example, one with the same direction as the difference vector  $\mathbf{d}$  and the other with the same direction as the normalized difference vector  $\frac{\mathbf{d}}{norm}$ . The noise is further scaled by a hyperparameter  $s$  to control the magnitude of the perturbation. Combined with these search vectors, L-AutoDA is able to generate adversarial examples that are both effective and efficient.

## VI. DISCUSSION

**Expanded Experimental Validation.** Although our experimental framework, consisting of 20 generations with 10 individuals per generation, has yielded results surpassing those of manually-designed state-of-the-art algorithms, it has not fully tested the boundaries of our framework or LLMs. We will increase the number of generations and individuals to see if we can obtain better results. We aim to test these limits by increasing the population size and the number of generations. Additionally, initializing the search process with

### Algorithm 2 `generate()`

- 1: **Input:** original example  $\mathbf{x}_0$ , adversarial starting point  $\mathbf{x}_1$ , standard normal noise  $\mathbf{n}$ , hyperparameter  $s$
- 2: **Output:** A new proposed example  $\mathbf{x}$
- 3:  $\mathbf{d} \leftarrow \mathbf{x}_0 - \mathbf{x}_1$
- 4:  $norm = \max(\|\mathbf{d}\|_2, \|\mathbf{n}\|_2)$
- 5:  $\mathbf{x} \leftarrow \mathbf{x}_1 + s(\mathbf{d} + \frac{\mathbf{d}}{norm}) + s(\mathbf{n} + s\frac{\mathbf{n}}{norm})$

existing algorithms and subsequently refining them represents a promising avenue for further experimentation.

**Broader Algorithm Search Space.** or expediency and as an initial attempt for automated attack algorithm design using LLMs into the automated design of attack algorithms using LLMs, we confined the search space to that defined by the `generate()` function. However, this narrow scope may restrict the discovery of optimal algorithms. Future work will seek to exploit the full potential of LLMs by allowing them to craft comprehensive algorithms without such constraints.

**Enhancing Prompt Adaptability.** Our methodology employed a set of static prompts to assist LLMs in algorithm generation. However, the fixed prompts may not be the best prompts for LLMs to generate algorithms. The effectiveness of these prompts, however, may not represent an optimal use of LLM capabilities. The concept of chain-of-reasoning, which underpins our work and AEL, suggests a close relationship with adaptive prompt generation. Investigating methods of dynamically generating prompts is an objective of our ongoing research.

**Addressing Limitations.** While the synthesis of programs using large language models is the focus of our research, it is not without its drawbacks. These models may occasionally yield unsatisfactory outcomes, albeit at a lower rate than traditional approaches. Improving the specificity of constraints within the prompts to ensure the validity of the algorithms produced will be an integral part of our forthcoming efforts.

## VII. CONCLUSION

In this paper, we have successfully demonstrated the innovative application of LLMs for the automatic design of decision-based adversarial attack algorithms. By leveraging the AEL framework, we have not only streamlined the algorithmic design process, but also achieved a significant reduction in the time and expertise required to develop effective adversarial attacks. Our approach, encapsulated in the L-AutoDA framework, represents a paradigm shift in the field of adversarial machine learning, showcasing the untapped potential of LLMs in the realm of security and algorithm synthesis.

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