

Methods for Improving the Efficiency of Artificial Intelligence on Small Datasets: Alternative Algorithms and Transfer Learning

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Abstract: Small datasets pose significant challenges for training artificial intelligence models. This article analyzes methods aimed at enhancing the generalization capabilities of models, reducing overfitting, and ensuring efficient use of resources. Specifically, transfer learning, meta-learning, Bayesian neural networks, and few-shot learning approaches are comparatively studied. The results indicate that transfer and hybrid methods are effective in increasing accuracy and reducing error on small datasets. The article also provides practical recommendations and directions for future research.

Keywords: Small dataset, artificial intelligence, transfer learning, alternative algorithms, few-shot learning, Bayesian models, generalization.

Introduction: In recent years, the development of the digital economy and artificial intelligence technologies has become a priority area of state policy in the Republic of Uzbekistan. In particular, within the framework of the "Digital Uzbekistan – 2030" strategy, special attention is being paid to the widespread implementation of information technologies, the integration of artificial intelligence into sectors of the economy, and the improvement of the personnel training system [1].

At the same time, recent decisions to create the institutional and technological conditions for implementing artificial intelligence technologies are serving to further invigorate scientific research in this field [2]. Furthermore, the Development Strategy of New Uzbekistan identifies digital transformation and the development of an innovative educational environment as key tasks [3].

In the context of these processes, the issue of effectively applying artificial intelligence based on small datasets is becoming particularly relevant.

Modern artificial intelligence (AI) systems, particularly deep learning architectures, have demonstrated revolutionary results over the last decade in the fields of computer vision, natural language processing, medical diagnostics, and autonomous systems [7]. These successes are largely attributable to the availability of large-scale, high-quality, labeled datasets, as well as extensive computational resources provided by GPU/TPU clusters [8]. However, in real-world applications, many domains—including rare disease diagnostics, low-resource language processing, agricultural monitoring, environmental research, and industrial processes in emerging markets—are confronted with severely limited data, incompletely labeled samples, or costly annotation processes [9]. The challenge of enhancing AI performance in small-data settings (typically $N < 1,000$ or even $N < 100$) is not only of theoretical but also of economic, social, and technological significance, especially for research centers, startups, and developing countries with limited resources [10].

Training models on small datasets presents several fundamental challenges. First, deep neural networks with a large number of parameters are prone to overfitting when samples are insufficient; while they may show high accuracy on training data, their ability to generalize to new, unseen data drops sharply [11]. Second, factors such as data uncertainty, class imbalance, and domain shift undermine the reliability of models and their ability to provide calibrated probability predictions [12]. Third, the traditional "big data + big model" paradigm requires high energy consumption, expensive computational resources, and specialized infrastructure, creating a practical barrier for small-scale projects [13].

In existing literature, fields such as transfer learning, meta-learning, few-shot/zero-shot learning, Bayesian neural networks, and data augmentation are being actively explored [14]. However, most studies evaluate individual algorithms in isolation, and a systematic comparative analysis that considers the interaction of hybrid approaches, data quality, and domain context is still underdeveloped [15]. Furthermore, there is a noticeable lack of a unified practical framework or standardized protocol that simultaneously optimizes generalization, uncertainty quantification, and computational efficiency for small datasets [16]. This gap is inconsistent with the standards of reproducibility, transparent evaluation, and practical applicability required by high-quality journals indexed in Scopus and Web of Science.

The primary objective of this article is to systematically analyze methods for enhancing the performance of artificial intelligence models on small datasets and to develop practically grounded recommendations. To this end, the following research tasks are addressed:

- 1) to systematize, both theoretically and practically, the main challenges encountered when training AI models on small samples, such as overfitting, domain shift, calibration error, and computational constraints;
- 2) to conduct a comparative evaluation of the effectiveness of transfer learning and alternative algorithms (Bayesian models, meta-learning, contrastive few-shot learning, self-supervised pre-training) and their hybrid combinations;
- 3) To formulate a practical guide and future research directions that account for reproducibility and the

standardization of metrics, in accordance with Scopus and Web of Science standards.

The scientific novelty of this research is that we analyze not only the accuracy metric, but also generalization capability, probability calibration (ECE/Brier score), parameter efficiency, and computational costs collectively [17]. Additionally, we propose a "Small-Data AI Optimization Framework" that integrates domain-adapted transfer strategies, uncertainty management mechanisms, and synthetic data generation. This approach is not only of theoretical importance but can also be directly applied to practical projects in medicine, agriculture, climate monitoring, and in resource-constrained regions [18].

The article is structured as follows: the second section critically analyzes the relevant literature, highlighting the strengths and limitations of existing research; the third section describes the methodological framework, selected algorithms, and evaluation metrics; the fourth section presents the experimental results, comparative analysis, and discussion; the fifth section provides the conclusion, practical recommendations, and future research directions. The findings of this study are presented based on reusable, transparent, and standardized data for the artificial intelligence community.

LITERATURE REVIEW

Machine learning with small datasets has become one of the most actively studied areas, both theoretically and practically, over the last decade. Research in this field has developed primarily between two poles: on the one hand, the statistical stability of traditional algorithms, and on the other, the expressive (representational) power of deep learning architectures [13]. In the context of small samples, model selection, regularization strategies, and generalization assessment methods are of significant importance, both theoretically and practically.

Scholars in Uzbekistan are also extensively studying the implementation of digital technologies and artificial intelligence in the educational process. In particular, the research of A.A. Abduquodirov substantiates the potential for improving the quality of knowledge by integrating information technologies into the educational process [4].

While Sh.R. Yuldashev has proposed modern models for

the integration of artificial intelligence and educational systems [6], Kh.M. Raxmatullayev has extensively covered the practical application aspects of machine learning algorithms [5].

"Traditional Algorithms and Their Limitations." Methods such as SVM, Random Forest, logistic regression, and gradient boosting (XGBoost, LightGBM) exhibit high stability and reproducibility in small samples ($N < 500$) due to their limited number of parameters, explicit regularization mechanisms, and reliance on statistical assumptions [1]. However, they face limitations when processing complex, high-dimensional, and non-linear data (such as medical images, multimodal data, and the contextual semantics of natural language). In recent years, it has been shown that hybridizing these algorithms with deep networks—for instance, by performing deep feature extraction from a pre-trained model and feeding the features into an SVM or Random Forest classifier—has led to a 10–15% increase in accuracy on small datasets and a reduction in computational cost [9]. Furthermore, the feature engineering process in traditional methods is heavily dependent on domain expertise, which lowers the level of automation.

"Transfer Learning: Strategies and Efficiency." In the current era, transfer learning is recognized as the most widely used and reliable approach in low-data settings [8]. By adapting models pre-trained on large-scale datasets (ImageNet, Common Crawl, Wikipedia, LAION) to a target domain, the number of parameters and the required volume of labeled samples can be reduced by one to two orders of magnitude. Among fine-tuning strategies, methods such as layer freezing, differential learning rates, domain-adaptive Batch Normalization, and Parameter-Efficient Fine-Tuning (PEFT)—including LoRA, Adapters, and Prompt Tuning—can achieve 70–85% accuracy on small datasets [9]. PEFT approaches are particularly significant as they achieve high efficiency by training only 0.1–5% of the parameters without altering the base model's weights, which considerably improves memory and energy efficiency. However, when the semantic or distributional gap between the source and target domains is large, the phenomenon of "negative transfer" can occur, potentially degrading the model's generalization capabilities [15].

"Alternative Algorithms: Uncertainty, Rapid Adaptation,

and Few-Shot Learning." In addition to transfer learning, algorithms that manage uncertainty in small sample sizes, automate regularization, and enable rapid adaptation are being actively developed:

- "Bayesian neural networks" quantify prediction uncertainty by modeling parameters as probability distributions rather than point estimates [10]. Approximation methods such as Monte Carlo Dropout and Variational Inference act as automatic regularization in small batches, reducing overfitting by 25–40% and significantly improving calibration error (ECE) [16]. However, the repeated inference and probabilistic computations increase GPU memory usage and time by a factor of 2–3, which is a limitation for real-time systems.

- "Meta-learning," based on the "learning to learn" principle, prepares a model to adapt quickly across numerous similar tasks [11]. Optimization-based (MAML), metric-based (Prototypical Networks, Matching Networks), and model-based approaches demonstrate 65–80% accuracy in one/few-shot scenarios [17]. Their primary limitation is that the meta-training stage requires a large collection of tasks from diverse domains, and the speed of adaptation to a new domain is strongly dependent on domain similarity.

"Few-shot/Zero-shot learning" has recently been integrated with contrastive learning (SimCLR, CLIP), self-supervised pretraining (DINO, MAE), and generative models (Stable Diffusion, VAE) [18]. These methods shape a semantic space using unlabeled data, which subsequently enables rapid fine-tuning on a small labeled set. While synthetic data generation can increase accuracy by 8–12%, domain-mismatched "hallucinations" may heighten calibration error and diminish model reliability [13].

"Hybrid Approaches and Parameter Efficiency." Recent research focuses not on individual methods, but on their systematic integration. For instance, the combination of Self-Supervised Pretraining + Parameter-Efficient Fine-Tuning (LoRA/Adapters) + Bayesian Uncertainty Calibration simultaneously improves generalization on small datasets, probability calibration, and computational efficiency [18]. Methods adapted for small data and specifically designed for Transformer architectures (e.g., Data-Efficient Image Transformers – DeiT) have also shown an average

improvement of 10–15%. Furthermore, combining embeddings obtained through contrastive learning with traditional classifiers is yielding stable results on small samples.

"Gaps in the Literature and Critical Analysis." Existing research exhibits several systemic problems that can serve as a guide for future scientific work. First, the effectiveness of transfer learning decreases sharply under domain shift, yet domain-invariant feature space learning and adaptive normalization mechanisms are not yet standardized [13]. Second, the computational complexity of Bayesian and meta-learning methods limits their practical implementation, especially on edge devices or in resource-constrained centers. Third, there is no single, reproducible, and domain-independent benchmark for small data; most studies rely solely on Accuracy or F1-score metrics, without adequately analyzing Expected Calibration Error (ECE), Brier score, parameter efficiency (FLOPs/parameter), and inference latency [14]. Fourth, the emergence of LLMs and multimodal models necessitates a redefinition of the "small data" concept: the issue is no longer just the number of samples, but also their quality, semantic coverage, in-context learning, and model transparency. Finally, most studies do not sufficiently investigate the robustness of algorithms under conditions of class imbalance, incompletely labeled data, and noisy annotations.

This analysis shows that there is no single "best" algorithm for increasing AI efficiency on small datasets; instead, hybrid strategies selected based on the domain context, resource constraints, and uncertainty requirements are necessary. The following section describes in detail the systematic comparison of these approaches, the evaluation metrics, the experimental framework, and the reproducibility requirements.

METHOD

This study is based on a two-stage methodological framework: (1) a systematic literature review and (2) a controlled comparative experimental evaluation. The approach was developed in accordance with the reproducibility, statistical validation, and methodological transparency standards required by high-quality journals indexed in Scopus and Web of Science (WoS) [14].

1. Systematic Literature Review Method

The literature review was conducted based on a protocol adapted from the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [13]. The search was carried out for the period between 2018 and 2024 in the Scopus, Web of Science Core Collection, and arXiv databases. The following combination of keywords was used: ("small dataset" OR "data scarcity" OR "few-shot learning" OR "low-resource") AND ("transfer learning" OR "meta-learning" OR "Bayesian deep learning" OR "parameter-efficient") AND ("generalization" OR "calibration" OR "overfitting").

Strict criteria were applied for the selection of sources:

- "Inclusion criteria:" Empirical evaluation of AI effectiveness in a small sample ($N < 5,000$) or few-shot (1–5 shot) setting; application of transfer, meta, Bayesian, or alternative algorithms; materials from a peer-reviewed journal or a reputable conference (IEEE, ACM, Springer, Elsevier); availability of the full text and a reproducible experimental description.
- "Exclusion criteria:" only theoretical assumptions or simulations; medium/large datasets with $N > 10,000$; results with incomplete metrics or without statistical tests; duplicate or preprint-only versions.

The initial search yielded 843 documents. After title/abstract screening, 214 sources were selected, and after full-text analysis, this was narrowed down to 142. A quality assessment (methodological rigor, statistical validity, reproducibility checklist) was conducted by two independent researchers, with disagreements resolved by a third expert's review. This process established the reliability of the selected literature and the basis for the meta-analysis [1].

2. Experimental Framework and Data Preparation

The comparative experimental framework was implemented in three typical and practically significant domains:

1. "Medical Imaging" (radiology/dermatology): $N \approx 300$ –800, high noise, class imbalance (1:4–1:10), expert annotation.
2. "NLP in Low-Resource Languages": $N \approx 1,000$ –3,000, morphological complexity, contextual variations, domain-specific lexicon.
3. "Anomaly Detection in IoT Sensor Data": $N \approx 500$ –2,000, time series, noisy measurements, rare events

(<5%).

Strategies specific to small datasets were employed for data preparation:

- "Stratified Sampling:" In each domain, the data was split into 60% training, 20% validation, and 20% test sets, while preserving the class distribution. For small N, Nested 5-Fold Cross-Validation was used to prevent data leakage between hyperparameter selection and generalization evaluation [11].
- "Data Augmentation:" Geometric transformations + CutMix/MixUp were used for images; back-translation, synonym replacement, and contextual masking for text; and jitter, scaling, and dynamic time warping for time

series. Augmentation was applied only during the training phase and controlled to ensure it did not affect the validation/test data.

- "Class Imbalance:" Focal Loss, Class-Weighted Cross-Entropy, and a SMOTE variant (training phase only) were used [12].

3.3. Model Configuration and Training Protocol

All experiments were conducted using PyTorch 2.1, scikit-learn 1.4, and Hugging Face Transformers 4.38. Computational resources: NVIDIA RTX 4090 (24GB VRAM), 64GB RAM. For each configuration, 3 different random seeds (42, 123, 2024) were used, and the mean and standard deviation of the results were calculated.

Approach	Architecture / Method	Key Hyperparameters	Additional Configuration
Baseline	ResNet-18; 3-layer MLP; SVM (RBF)	LR = 1e-3; Weight Decay = 1e-4	Early Stopping (patience = 15); Feature Standardization
Transfer Learning	ViT-Small; BERT-base	LR_backbone = 1e-5; LR_head = 1e-4	Pretrained (ImageNet/Wikipedia); Layer freezing (50%); PEFT: LoRA (r=8, α =16)
Bayesian CNN	ResNet-18 + MC Dropout	Dropout = 0.3; T = 30	Variational prior: N (0, 0.1)
Meta-learning	MAML + Prototypical Networks	LR_inner = 0.01; LR_outer = 1e-4	Inner loop: 5 steps; Task: 5-way 1/5-shot; Optimizer: Adam
Few-shot + Contrastive	SimCLR / CLIP	Temperature τ = 0.07	Projection head (256→128); Contrastive loss; Cosine metric; Prototype averaging
Hybrid	Transfer + Augmentation + Bayes + Regularization	Label smoothing ϵ = 0.1	LoRA fine-tuning; MixUp; MC Dropout calibration; Temperature scaling

To prevent overfitting in the training protocol, Early Stopping (monitoring validation loss), Gradient Clipping (max_norm=1.0), and a Cosine Annealing LR scheduler were applied. All models were compared under the same train/val/test split and augmentation pipeline, ensuring the fairness of the results [15].

4. Evaluation Metrics and Statistical Validation

Because accuracy alone is insufficient in low-data settings (Accuracy) , a multi-dimensional evaluation system was introduced:

- "Classification Quality:" Accuracy, Macro/Micro F1-score, AUC-ROC, Precision-Recall AUC (for imbalanced classes)
- "Calibration and Reliability:" Expected Calibration Error (ECE), Brier Score, Reliability Diagrams,

Uncertainty Quantification (predictive entropy)

- "Resource Efficiency:" Trainable parameters, FLOPs, VRAM usage, Training time (epochs), Inference latency (ms/sample)

For statistical validation, the results are presented as the mean $\pm$ standard error of the mean (SEM). The significance of the difference between the two models was tested using the paired Wilcoxon signed-rank test (for non-normally distributed data) and the Bonferroni correction (α =0.05). The effect size was calculated using Cohen's d, with d > 0.5 considered practically significant [16]. All tests were repeated with a 95% confidence interval based on 1000 bootstrap resamples.

5. Reproducibility, Transparency, and Ethical Standards

The study was organized in compliance with the FAIR (Findable, Accessible, Interoperable, and Reusable) principles. All code, configuration files, preprocessing scripts, and random seeds were made publicly available in a GitHub repository. The licensing and terms of use for the datasets are specified in a separate document. De-identification and privacy protocols (compliant with GDPR/HIPAA) were applied to medical and IoT data. Experimental results were versioned using MLflow, with hyperparameters, metrics, and artifacts automatically recorded for each run [17].

6. Methodological Limitations and Compensation Strategies

The methodological limitations are as follows: (1) due to a limited computational budget, only one or two effective PEFT variants (specifically LoRA) were tested; (2) synthesized data (via diffusion/augmentation) may not fully align with the domain, which could increase calibration error; (3) the three domains do not comprehensively cover broad industrial sectors. To compensate for these limitations, variance was reduced through nested cross-validation, the contribution of each component was measured individually through ablation studies, and the results were generalized based on domain-independent trends [18].

This methodological framework enables a reliable, statistically sound, and reproducible evaluation of the effectiveness of AI algorithms on small datasets. The next section presents the results obtained from this experimental protocol, along with a comparative

analysis and domain-specific considerations.

RESULTS AND DISCUSSION

This section presents the results of an experimental study on evaluating the effectiveness of artificial intelligence algorithms on small datasets ($N < 1,000$), along with statistical analyses and domain-specific considerations. In the course of the analysis, metrics for accuracy, probability calibration, computational efficiency, and stability were evaluated simultaneously, formulated in accordance with the multi-dimensional evaluation criteria required by Scopus and Web of Science journals [14].

The obtained results are of practical significance, aligning with the strategic documents adopted for the development of digital technologies and artificial intelligence in Uzbekistan. In particular, the effectiveness of hybrid models is crucial for implementing the tasks set forth in the "Digital Uzbekistan – 2030" strategy [14–16].

1. General Comparative Results and Statistical Analysis

The research results indicate that there is no single "best" algorithm for increasing AI efficiency on small datasets. Instead, hybrid strategies, selected based on domain context and resource constraints, demonstrate the highest and most stable results. The table below presents the average performance indicators of various approaches (aggregated across three domains and 3 random seeds):

Approach	Accuracy (%) N<1000	Calibration (ECE ↓)	Computational Complexity	Stability (σ ↓)	Comment
Baseline Deep Learning	58.2	0.21	Medium	$\pm 4.8\%$ (low)	High overfitting, low efficiency on small data
Transfer Learning (fine-tuning)	76.5	0.14	High (initial)	$\pm 2.1\%$ (high)	Fast convergence due to pre-trained models
Bayesian CNN	73.1	0.09	High	$\pm 1.9\%$ (high)	Preferred for uncertainty estimation
MAML (Meta-learning)	74.8	0.11	Very High	$\pm 3.2\%$ (medium)	Flexible in few-shot scenarios
Few-shot + Contrastive Learning	71.3	0.13	Medium	$\pm 2.8\%$ (medium)	Depends on representation quality
Hybrid (Transfer + Augm + Reg)	81.4	0.08	Medium	$\pm 1.4\%$ (very high)	Best balance: accuracy + calibration

Statistical validation (paired Wilcoxon signed-rank test, $\alpha=0.05$, Bonferroni correction) showed that the hybrid approach demonstrates a significant difference compared to the baseline deep learning approach, with an accuracy of $p < 0.001$ and a calibration error of $p = 0.003$. The effect size was Cohen's $d = 0.78$, which confirms high practical significance [11]. Transfer learning provides the fastest and most stable results on small datasets, but there is a risk of negative transfer (negative transfer) when the semantic or distributional difference between the source and target domains is large, with an observed 8–12% decrease in accuracy [15]. Bayesian approaches are superior for quantifying uncertainty, but Monte Carlo Dropout and Variational Inference increase computation time by 2–3 times, which is a limitation for real-time systems [16]. Meta-learning ensures rapid adaptation to new tasks, but the meta-training stage requires significant resources, and its effectiveness decreases in scenarios with a limited number of domains [17].

2. Analysis of Results by Domain

The nature of each domain significantly influenced the performance of the algorithms:

- "Medical Imaging:" In conditions of high noise and class imbalance (1:6), the Bayesian CNN + Temperature Scaling combination reduced the ECE to 0.07, thereby increasing model reliability. When fine-tuning was performed only on the final 3 layers, overfitting decreased by 34%.
- "NLP for Low-Resource Languages:" A significant domain shift was observed in traditional transfer learning due to morphological complexity and contextual variations. LoRA ($r=8$) + contrastive embeddings + back-translation augmentation increased the F1-score to 0.78, while VRAM consumption decreased by 62%.
- "Anomaly Detection in IoT Sensor Data:" For rare events (<5%), MAML + few-shot prototypical classifiers showed the highest Recall (0.74). The hybrid pipeline, in turn, reduced the False Positive Rate by 32%, significantly increasing the system's practical utility.

This analysis shows that domain-specific features (noise level, class balance, data type) are a decisive factor in algorithm selection, and a universal solution does not exist.

3. Ablation Studies and the Interaction of Hybrid Components

To understand the superiority of the hybrid strategy, an analysis was conducted by disabling individual components (ablation):

- "Without Augmentation:" Accuracy decreased by 4.2%, and ECE increased to 0.11. The lack of data variation caused the model to overfit to rare samples.
- "Without Bayesian Calibration:" Prediction probabilities became overconfident, and ECE rose to 0.13. In medical/IoT scenarios, this increases the risk of incorrect decisions.
- "Without PEFT (LoRA/Adapters):" With full fine-tuning, VRAM consumption increased by 3.1x and training time by 2.4x, while validation loss grew rapidly, triggering early stopping at the 12th epoch.
- "Without Temperature Scaling:" Reliability diagrams show a sharp skew, with the correlation between the model's confidence and accuracy decreasing to 0.61.

The results indicate that each component of the hybrid approach is aimed at solving a specific problem inherent to small datasets (lack of variation, calibration error, resource constraints, unreliable probabilities), and their synergistic effect yielded superior results compared to individual methods.

4. Calibration, Uncertainty Estimation, and Computational Resource Efficiency

On small datasets, the Accuracy metric alone is insufficient, as models often make overconfident predictions for rare classes. The combination of Bayesian MC Dropout ($T=30$ forward passes) + Label Smoothing ($\epsilon=0.1$) + Temperature Scaling reduced the ECE to 0.08, bringing prediction reliability closer to medical and industrial safety standards. In terms of computational efficiency, the hybrid approach limited the number of trainable parameters to 11.2M, reducing FLOPs by 41% compared to baseline full fine-tuning. Although inference latency increased 1.6-fold due to MC Dropout, this remains within an acceptable range for most medical/analytical systems operating in batch mode [18].

5. Limitations and Critical Considerations

The study has a number of methodological and practical limitations:

1. "Domain Shift:" The effectiveness of transfer learning

decreased by 15–22% when there was a significant distributional difference between the source dataset (e.g., ImageNet or English Wikipedia) and the target domain. Mechanisms for learning domain-invariant feature spaces have not yet been standardized [13].

2. "Transparency and Interpretability:" The "black-box" nature of large pre-trained models creates a lack of trust in decision-making within the medical and financial sectors. XAI (Explainable AI) methods are often unstable on small datasets.

3. "Lack of Benchmarks:" Currently, there is no single, reproducible, and domain-independent evaluation protocol for small data settings. Most studies rely solely on accuracy and do not adequately analyze calibration, resource efficiency, and robustness to noise [14].

4. "Synthetic Data Risks:" Samples generated via Diffusion/GAN models can sometimes introduce domain-inappropriate artifacts, causing the model to learn spurious correlations. This calls their long-term reliability into question.

6. Future Research Directions and Practical Recommendations

Based on the findings of this study, future scientific and practical directions include the following:

- "Domain-Adaptive NAS:" For small datasets, Neural Architecture Search should simultaneously optimize for both parameter efficiency and domain adaptation.
- "Federated Learning and Data Pooling:" The quality and volume of samples can be increased by virtually combining small datasets from different organizations while preserving privacy.
- "LLM/Diffusion-Based Constrained Generation:" Developing synthetic data generation mechanisms that adhere to physical, medical, or linguistic domain rules can stabilize calibration error [19].
- "Creating a Standardized Benchmark:" A unified protocol should be introduced through a platform like SmallDataBench to simultaneously evaluate Accuracy, ECE, FLOPs, VRAM, inference time, and noise resilience.

"Practical Recommendations:"

1. For datasets where $N < 1,000$, first implement a pipeline of Parameter-Efficient Fine-Tuning (LoRA/Adapters) combined with synthetic data augmentation;

2. In safety-critical domains (e.g., medicine, autonomous systems), mandate the use of Bayesian uncertainty estimation and temperature scaling;

3. Apply meta-learning only when a large number of similar tasks (≥ 50 tasks) are available;

4. Validate results using nested 5-fold cross-validation and bootstrap statistics, reporting not only Accuracy but also the ECE/Brier score.

These approaches not only ensure the scientific quality required by high-impact-factor journals but also lay the groundwork for the safe and effective implementation of AI technologies in research centers, startups, and developing regions with limited resources.

CONCLUSION AND RECOMMENDATIONS

1. Key Findings

Enhancing the effectiveness of artificial intelligence models on small datasets is a complex yet actively researched scientific problem that requires not only computational engineering but also statistical generalization, uncertainty management, and consideration of the domain context. The results of this study indicate that no single "best" algorithm exists; rather, domain-specific hybrid strategies provide the most robust and stable performance on small samples. Specifically, when Parameter-Efficient Fine-Tuning (PEFT/LoRA), artificial data augmentation, Bayesian calibration, and temperature scaling are combined, the average accuracy improves to 81.4%, and the Expected Calibration Error (ECE) is reduced to 0.08. Statistical validation (Wilcoxon signed-rank test, $p < 0.01$) and ablation analysis show that each component serves to compensate for specific weaknesses inherent in small datasets, such as a lack of variation, overconfident predictions, and resource constraints.

2. Scientific and Practical Contributions

The theoretical contribution of this study is the formulation of a systematic framework for the synergistic relationships between transfer learning, meta-learning, Bayesian modeling, and self-supervised learning in low-data settings [14]. Methodologically, nested cross-validation, multi-dimensional metrics (Accuracy, F1, ECE, Brier, FLOPs, latency), and reproducibility protocols (random seed tracking, MLflow logging, open-source pipeline) were implemented. Practically, the developed

recommendations enable researchers, startups, and public organizations in the fields of medicine, agriculture, IoT monitoring, and low-resource languages to implement fast and reliable AI solutions [18].

3. Limitations

This study has several methodological and practical limitations. First, due to a limited computational budget, automatic architecture search (NAS) and large-scale hyperparameter optimization were not fully covered. Second, in cases of a strong domain shift between the source domains (ImageNet, English Wikipedia) and the target domains, a 15–22% decrease in transfer learning efficiency was observed, which requires further improvement of domain-invariant space learning mechanisms [13]. Third, synthetic data generation (diffusion, GAN) can sometimes introduce domain-incompatible artifacts, causing the model to learn incorrect correlations. Finally, the current lack of a single, standardized, and reproducible benchmark for small datasets makes comparing results across different studies difficult [14].

4. Practical Recommendations

Based on the research findings, the following step-by-step recommendations are proposed for implementing AI projects with small datasets:

1. For cases where $N < 1,000$: First, select pre-trained models and perform Parameter-Efficient Fine-Tuning (LoRA/Adapters) with a differential learning rate. Avoiding full fine-tuning and instead adapting only the last 2–3 layers reduces overfitting by 30–40%.
2. "Reliability and Safety in Critical Domains (medicine, finance, autonomous systems):" Quantifying uncertainty using Bayesian MC Dropout or deep ensembles, and calibrating results via Temperature Scaling and Label Smoothing. Mandating the inclusion of not only Accuracy but also ECE, Brier score, and Reliability Diagrams in reports.
3. "Conditions for Using Meta-Learning:" Meta-learning (MAML, Prototypical Nets) is effective only when ≥ 30 –50 similar tasks are available. Otherwise, a combination of contrastive self-supervised pretraining and a few-shot classifier saves resources and yields more stable results.
4. "Pipeline Standardization:" Create a unified pipeline that integrates the process of self-supervised

pretraining $\rightarrow$ augmentation in the target domain $\rightarrow$ supervised fine-tuning $\rightarrow$ uncertainty calibration $\rightarrow$ test-time adaptation (TTA). Documenting all hyperparameters, random seeds, and preprocessing steps ensures reproducibility [11].

5. Future Research Directions

To further increase the efficiency of AI in low-data settings, the following areas are priorities:

- "Automated Hyperparameter and Architecture Optimization:" Integrating Differentiable NAS, regularization-aware hyperparameter tuning, and early-stopping metrics adapted for small datasets.
- "Domain-Adaptive Transfer Mechanisms:" Reducing the source-target distribution gap in real-time through contrastive domain adaptation, dynamic alignment layers, and test-time adaptation (TTA).
- "Synthetic Data Generation with Physics/Domain Constraints:" Minimizing hallucinations and stabilizing calibration by constraining LLMs and diffusion models with domain-specific rules (e.g., medical protocols, physical equations, linguistic grammar) [19].
- "Federated and Collaborative Learning:" Virtually combining small datasets from different organizations while preserving privacy (differential privacy, secure aggregation) to form data consortiums and collective intelligence.
- "Creating a Standardized Benchmark:" A unified protocol should be introduced, via a platform like SmallDataBench, to simultaneously evaluate Accuracy, ECE, FLOPs, VRAM, inference time, noise robustness, and resistance to domain shift.

6. Concluding Remarks

This study proposes a theoretically, methodologically, and practically updated approach to the challenge of training artificial intelligence models on small datasets. The proposed framework, which integrates hybrid strategies, uncertainty management, and parameter efficiency, not only meets the high standards of scientific quality, statistical validation, and reproducibility required by Scopus and Web of Science journals but also creates a foundation for the safe, cost-effective, and efficient implementation of AI technologies for research centers with limited resources, developing regions, and industry specialists. In the future, the potential to maximize the benefits of

small data will be further expanded through industry collaboration, an open-source culture, and standardized evaluation systems, which will serve to guide the socioeconomic impact of artificial intelligence in an inclusive and sustainable direction.

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