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Uncertainty Estimation in Deep Learning Models for Reliable Autism Detection: Enhancing Clinical Trust Through Probabilistic Confidence Measures

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Abstract

The deployment of deep learning models for autism spectrum disorder detection in clinical settings requires not only high accuracy but also reliable uncertainty quantification to support informed decision-making by healthcare professionals. This research presents a comprehensive framework for uncertainty estimation in deep learning models for autism detection, integrating multiple probabilistic approaches to provide calibrated confidence measures that align with real-world diagnostic reliability. Our methodology combines Monte Carlo dropout, deep ensembles, and temperature scaling techniques within a unified architecture specifically designed for the complex, multimodal nature of autism behavioral data. The framework was evaluated on a diverse dataset of 7,200 children from 15 clinical sites, employing both behavioral assessment scores and video-based interaction data. Results demonstrate that our uncertainty-aware models achieve 93.8% diagnostic accuracy while providing well-calibrated confidence estimates that closely match empirical accuracy across different confidence thresholds. The uncertainty measures

successfully identified 89.4% of misclassified cases through low-confidence predictions, enabling selective referral to human experts for ambiguous cases. Clinical validation with 45 practitioners showed that incorporating uncertainty information increased diagnostic confidence by 42% and improved appropriate reliance on AI recommendations. The research establishes that systematic uncertainty estimation significantly enhances the practical utility and safety of AI-assisted autism diagnosis by providing transparent reliability measures that support clinical decision-making while maintaining high performance standards. This work bridges the gap between computational model development and clinical implementation requirements, addressing critical needs for trustworthy AI in healthcare applications where diagnostic decisions carry profound implications for children's developmental trajectories.

Keywords: Uncertainty Estimation, Deep Learning, Autism Detection, Bayesian Neural Networks, Confidence Calibration, Reliable AI, Clinical Decision Support

1 Introduction

The integration of deep learning models into autism spectrum disorder diagnosis represents a promising frontier in computational psychiatry, yet the transition from research validation to clinical deployment faces significant challenges related to model reliability and trustworthiness. While contemporary deep learning approaches have demonstrated remarkable classification accuracy on benchmark datasets, their practical utility in clinical settings remains constrained by the absence of meaningful uncertainty quantification that aligns with healthcare professionals' decision-making processes. The black-box nature of these models, combined with their tendency to produce overconfident predictions even when incorrect, creates substantial barriers to clinical adoption where diagnostic decisions carry profound implications for children's developmental trajectories and intervention planning. This research addresses the critical need for reliable uncertainty estimation in autism detection models, recognizing that clinical trust depends not only on what decisions AI systems make but also on how confidently and reliably they make those decisions.

Uncertainty in deep learning models for autism detection arises from multiple sources that reflect both technical limitations and inherent complexities of the diagnostic task. Epistemic uncertainty, stemming from limitations in model knowledge and training data coverage, manifests particularly in cases with rare presentations or combinations of behavioral features not well-represented in training datasets. Aleatoric uncertainty, inherent in the data generation process itself, captures the natural variability in behavioral expressions, assessment conditions, and clinical interpretations that characterize autism diagnosis. Additionally, model uncertainty emerges from architectural choices, optimization processes, and the complex interactions between multimodal data sources typically

employed in comprehensive autism assessment. Understanding and quantifying these different uncertainty types is essential for developing AI systems that can appropriately communicate their limitations and support rather than replace clinical judgment.

The clinical significance of reliable uncertainty estimation extends beyond technical performance metrics to encompass fundamental aspects of healthcare delivery and patient safety. In autism diagnosis, where early intervention is crucial and misdiagnosis can have long-term consequences, uncertainty-aware AI systems can serve as valuable decision support tools that highlight cases requiring additional assessment, second opinions, or specialized expertise. By providing calibrated confidence measures, these systems can help clinicians allocate limited resources more effectively, prioritize complex cases for comprehensive evaluation, and maintain appropriate levels of human oversight in the diagnostic process. Furthermore, transparent uncertainty communication can facilitate more productive collaborations between AI systems and healthcare professionals, building trust through honest acknowledgment of limitations rather than presenting an illusion of infallibility.

This research introduces a comprehensive uncertainty estimation framework specifically designed for the unique challenges of autism detection, incorporating multiple probabilistic techniques within an integrated architecture that addresses both epistemic and aleatoric uncertainty sources. Our approach recognizes that effective uncertainty quantification in healthcare applications must balance statistical rigor with clinical interpretability, providing confidence measures that are both mathematically sound and meaningful to practitioners. The framework combines the theoretical foundations of Bayesian deep learning with practical implementation considerations for clinical workflows, enabling real-time uncertainty estimation without prohibitive computational demands.

The development of our uncertainty estimation methodology involved careful consideration of the multimodal nature of autism assessment data, which typically includes structured behavioral scores, unstructured clinical observations, and increasingly, video recordings of social interactions. Each data modality presents distinct uncertainty characteristics and requires specialized approaches for reliable confidence estimation. By developing modality-specific uncertainty techniques within a unified framework, we aim to provide comprehensive reliability measures that reflect the complex information integration processes inherent in expert clinical diagnosis.

The ethical dimensions of uncertainty-aware AI in autism diagnosis warrant particular attention, as these systems must navigate delicate balances between providing decisive guidance when appropriate and acknowledging limitations when necessary. Overly conservative uncertainty estimates could lead to unnecessary referrals and resource strain, while overly confident predictions might cause clinicians to defer excessively to AI recommendations. Our research addresses these ethical considerations through careful calibration of uncertainty thresholds and validation of clinical utility across diverse practice settings

and expertise levels.

This paper presents a comprehensive evaluation of our uncertainty estimation framework across multiple autism diagnostic models and clinical contexts, demonstrating significant improvements in reliability metrics while maintaining high diagnostic accuracy. We examine how uncertainty measures impact clinical decision-making processes, practitioner trust, and ultimately, diagnostic outcomes for children undergoing autism assessment. The research contributes both methodological advances in uncertainty quantification for medical AI and important insights into the practical requirements for deploying reliable, trustworthy AI systems in healthcare environments where safety and efficacy are paramount concerns.

2 Literature Review

The field of uncertainty estimation in deep learning has evolved substantially as researchers recognize that reliable confidence measures are essential for safe deployment in high-stakes applications. The foundational work by Gal and Ghahramani (2016) established Monte Carlo dropout as a practical approach for approximate Bayesian inference in deep neural networks, demonstrating that dropout during inference could generate uncertainty estimates by sampling from the posterior distribution. This seminal work provided accessible uncertainty quantification without the computational burden of traditional Bayesian methods, though questions remained about the quality and calibration of these estimates, particularly in complex medical applications.

The development of deep ensembles by Lakshminarayanan et al. (2017) represented another significant advancement, showing that training multiple models with different initializations could produce well-calibrated uncertainty estimates while maintaining high predictive performance. Their approach demonstrated that ensemble methods could capture both epistemic and aleatoric uncertainty effectively, though the computational cost of training multiple models presented practical challenges for clinical deployment. Subsequent research by Ovadia et al. (2019) provided comprehensive comparisons of uncertainty methods across various datasets and distribution shift scenarios, highlighting that no single approach consistently outperformed others across all evaluation metrics and that method effectiveness depended strongly on application context.

In medical imaging and diagnostic applications, uncertainty estimation has gained increasing attention as recognition grows that reliable confidence measures are crucial for clinical adoption. The work by Leibig et al. (2017) applied Bayesian deep learning to diabetic retinopathy screening, demonstrating that uncertainty estimates could identify cases requiring expert review and improve overall system reliability. Similarly, research by Kompa et al. (2021) examined uncertainty quantification in clinical prediction models, developing frameworks for communicating uncertainty to healthcare providers in clinically

meaningful ways. These studies established important foundations but often focused on relatively homogeneous data types rather than the multimodal, behaviorally complex data characteristic of autism assessment.

The specific application of uncertainty methods to autism research remains relatively unexplored despite the critical importance of reliability in diagnostic decisions. The pioneering work by Bone et al. (2016) on automated autism detection from video data achieved impressive accuracy but provided limited uncertainty quantification, focusing primarily on point estimates rather than probabilistic predictions. Subsequent research by Heinsfeld et al. (2018) applied deep learning to neuroimaging data from the ABIDE dataset, similarly emphasizing classification performance over reliability assessment. The gap between technical capability and clinical need for uncertainty-aware systems in autism diagnosis represents an important opportunity for methodological advancement.

Calibration techniques for improving the reliability of confidence estimates have developed alongside uncertainty quantification methods. The research by Guo et al. (2017) systematically examined modern neural network calibration, revealing that these models often produce overconfident predictions and introducing temperature scaling as an effective post-hoc calibration method. Their work established important benchmarks for calibration evaluation and demonstrated that simple techniques could significantly improve confidence reliability without affecting accuracy. However, the application of these calibration methods to medical diagnostics, where miscalibration could have serious consequences, requires careful validation and domain-specific adaptations.

Bayesian neural networks represent the theoretical gold standard for uncertainty estimation but have faced practical limitations due to computational complexity and implementation challenges. The work by Blundell et al. (2015) on Bayes by Backprop introduced practical variational inference methods for Bayesian neural networks, making Bayesian approaches more accessible for complex models. Subsequent research by Kristiadi et al. (2020) showed that incorporating uncertainty awareness into neural networks could improve robustness to distribution shift and adversarial examples, important considerations for clinical deployment where data characteristics may evolve over time.

The evaluation of uncertainty methods has evolved beyond simple accuracy metrics to encompass specialized reliability measures. The research by Lakshminarayanan et al. (2017) introduced proper scoring rules like negative log-likelihood and Brier score for comprehensive uncertainty assessment, while subsequent work by Kuleshov et al. (2018) developed calibration metrics that specifically measure how well confidence estimates match empirical accuracy. These evaluation frameworks provide essential tools for comparing uncertainty methods but require adaptation to medical contexts where different types of errors may have asymmetric costs and clinical implications.

Despite these advances, significant gaps remain in the literature on uncertainty estimation for autism detection. Most existing medical uncertainty research focuses on

imaging data rather than the behavioral and multimodal assessments central to autism diagnosis. The complex temporal dynamics of behavioral data, the integration of multiple information sources, and the need for clinically interpretable uncertainty communication present unique challenges that require specialized approaches. Furthermore, the practical implementation of uncertainty-aware systems in clinical workflows, including integration with electronic health records and communication to diverse stakeholders, remains underexplored.

Our research builds upon these foundations while addressing several critical limitations in existing approaches. We develop uncertainty estimation methods specifically designed for multimodal autism assessment data, integrate multiple complementary uncertainty techniques within a unified framework, and establish comprehensive evaluation metrics that assess both statistical reliability and clinical utility. By validating our approach across diverse clinical settings and practitioner groups, we ensure that the developed uncertainty measures provide meaningful support for real-world diagnostic decisions rather than merely technical improvements.

3 Research Questions

This research is guided by a comprehensive set of questions that address both technical and clinical dimensions of uncertainty estimation in deep learning models for autism detection. The primary research question investigates how different uncertainty quantification methods—including Monte Carlo dropout, deep ensembles, and Bayesian neural networks—perform in estimating prediction reliability for autism diagnostic models across various data modalities and clinical presentation types. This question encompasses not only the statistical quality of uncertainty estimates but also their computational efficiency, scalability to large datasets, and robustness to distribution shifts that may occur in real-world clinical deployment.

A crucial line of inquiry examines the calibration and reliability of uncertainty estimates produced by different methods, specifically investigating how well the predicted confidence levels align with empirical accuracy across various confidence thresholds and patient subgroups. We explore whether certain methods demonstrate systematic overconfidence or underconfidence patterns, how calibration varies across different demographic groups and clinical presentation types, and what techniques can effectively improve calibration without compromising diagnostic performance. Understanding these calibration characteristics is essential for developing uncertainty measures that clinicians can trust and incorporate into their decision-making processes.

Another important question concerns the clinical utility and interpretability of different uncertainty communication formats for healthcare professionals. We investigate how various presentations of uncertainty information—including confidence scores, probability

distributions, uncertainty visualizations, and categorical risk classifications—affect diagnostic decision-making, appropriate reliance on AI recommendations, and overall trust in AI-assisted diagnosis. This includes examining potential cognitive biases in uncertainty interpretation, understanding how clinical expertise influences uncertainty utilization, and developing optimal communication strategies for different healthcare contexts and user groups.

We also explore the relationship between uncertainty estimates and specific challenging diagnostic scenarios in autism assessment, investigating whether high-uncertainty predictions systematically correspond to clinically ambiguous cases, rare presentations, or boundary conditions between autism and other developmental conditions. This involves analyzing the clinical characteristics of high-uncertainty cases, understanding what factors contribute to diagnostic ambiguity from both computational and clinical perspectives, and determining whether uncertainty measures can reliably identify cases requiring specialized assessment or second opinions.

Furthermore, we investigate the practical implementation requirements for uncertainty-aware autism diagnostic systems in clinical settings, including questions of computational resource demands, integration with existing clinical workflows, training needs for healthcare professionals, and regulatory considerations for medical AI with explicit uncertainty quantification. Understanding these implementation challenges is essential for transitioning uncertainty estimation methods from research prototypes to clinically deployable tools that provide tangible benefits for patient care.

Finally, we consider the longitudinal aspects of uncertainty estimation in deployed systems, including how uncertainty characteristics evolve as models are updated with new data, how to monitor and maintain calibration over time, and what governance structures are needed to ensure ongoing reliability in real-world clinical use. This forward-looking perspective addresses the dynamic nature of healthcare environments and the need for uncertainty-aware systems that remain trustworthy throughout their operational lifespan.

4 Objectives

The primary objective of this research is to develop, implement, and comprehensively evaluate a unified framework for uncertainty estimation in deep learning models for autism spectrum disorder detection that provides reliable, well-calibrated confidence measures supporting clinical decision-making. This overarching objective encompasses the integration of multiple probabilistic techniques within an architecture specifically optimized for the multimodal data and complex diagnostic patterns characteristic of autism assessment. The framework aims to bridge the gap between technical uncertainty quantification methods and clinical utility requirements, enabling deployment of trustworthy AI systems in healthcare settings where diagnostic reliability is paramount.

A fundamental objective involves the systematic comparison and optimization of different uncertainty estimation methods for autism diagnostic models, including Monte Carlo dropout, deep ensembles, Bayesian neural networks, and temperature scaling techniques. This includes developing modality-specific uncertainty approaches for different data types used in autism assessment—such as behavioral scores, clinical observations, and video data—and creating integrated uncertainty measures that combine information across modalities in clinically meaningful ways. The methodological development emphasizes both statistical rigor and computational efficiency to ensure practical feasibility for clinical implementation.

Another crucial objective focuses on the calibration and validation of uncertainty estimates to ensure they provide accurate reliability information that aligns with empirical performance. This involves developing comprehensive calibration assessment protocols that evaluate uncertainty quality across different confidence levels, patient subgroups, and clinical presentation types. The calibration objective includes creating specialized metrics for medical applications where different types of misclassification may have asymmetric clinical consequences, and establishing calibration benchmarks that reflect real-world diagnostic reliability requirements.

We also aim to design and evaluate clinical communication strategies for uncertainty information that support appropriate reliance on AI recommendations and enhance diagnostic decision-making. This objective involves developing intuitive visualization methods for uncertainty presentation, creating categorical risk classification systems that translate probabilistic uncertainty into actionable clinical guidance, and validating these communication approaches with healthcare professionals across different clinical contexts and expertise levels. The communication design prioritizes clarity, clinical relevance, and integration with existing diagnostic workflows.

Furthermore, this research seeks to establish implementation guidelines and best practices for deploying uncertainty-aware autism diagnostic systems in clinical settings. This objective includes developing protocols for uncertainty monitoring and maintenance during clinical use, creating training materials for healthcare professionals on interpreting and utilizing uncertainty information, and establishing governance frameworks for uncertainty-aware medical AI that address safety, efficacy, and regulatory considerations. The implementation guidance aims to facilitate responsible adoption of uncertainty quantification techniques in healthcare environments.

Finally, we aim to contribute to the broader theoretical understanding of uncertainty in medical AI by developing evaluation frameworks that assess both technical performance and clinical impact, creating methodological approaches for uncertainty estimation in complex multimodal diagnostic tasks, and establishing principles for trustworthy AI development that prioritize reliability and transparency alongside accuracy. These theoretical contributions seek to advance the field of medical AI beyond mere performance

optimization toward comprehensive reliability assessment that supports safe and effective clinical deployment.

5 Hypotheses to be Tested

Based on extensive review of the literature and preliminary investigations, we formulated several testable hypotheses regarding the performance, utility, and impact of uncertainty estimation in deep learning models for autism detection. The primary hypothesis posits that integrated uncertainty estimation frameworks combining multiple probabilistic approaches will produce better-calibrated confidence estimates than single-method approaches, with calibration errors reduced by at least 40% while maintaining diagnostic accuracy within 1 percentage point of baseline models. We predict that this calibration improvement will be consistent across different data modalities and clinical presentation types, though the relative effectiveness of specific uncertainty methods may vary depending on data characteristics.

We hypothesize that uncertainty estimates will demonstrate strong correlation with diagnostic challenge level as assessed by clinical experts, with high-uncertainty predictions systematically corresponding to cases identified by clinicians as diagnostically ambiguous or requiring additional assessment. Specifically, we predict that uncertainty measures will identify at least 85% of misclassified cases through low-confidence predictions, enabling selective referral to human experts that could prevent a significant proportion of diagnostic errors in clinical deployment. This error detection capability is hypothesized to be particularly strong for cases involving rare behavioral presentations or complex comorbid conditions.

Regarding clinical utility, we hypothesize that incorporating uncertainty information into AI-assisted diagnosis will significantly improve appropriate reliance on AI recommendations compared to systems providing only binary predictions. We predict that healthcare professionals using uncertainty-aware systems will demonstrate better calibration between their trust in AI recommendations and actual AI performance, reducing both automation bias (over-reliance on correct AI suggestions) and algorithm aversion (under-utilization of valuable AI insights). This improved trust calibration is expected to be most pronounced for clinicians with moderate AI experience rather than complete novices or experts.

Another important hypothesis concerns the relationship between uncertainty characteristics and specific clinical factors in autism diagnosis. We predict that uncertainty patterns will systematically vary with patient age, symptom severity, and specific behavioral profile characteristics, reflecting the known challenges in diagnosing autism across different developmental stages and presentation types. Furthermore, we hypothesize that uncertainty measures can identify systematic gaps in training data coverage and highlight

patient subgroups where additional data collection would most improve model reliability.

We also hypothesize that the computational efficiency of different uncertainty methods will significantly impact their clinical implementation feasibility, with simpler approaches like temperature scaling demonstrating favorable trade-offs between uncertainty quality and resource requirements for real-time clinical use. However, we predict that more computationally intensive methods like deep ensembles will provide superior uncertainty estimation for particularly challenging cases, suggesting potential value in hybrid approaches that allocate computational resources based on case complexity.

Finally, we hypothesize that the longitudinal monitoring of uncertainty characteristics will provide valuable insights into model performance degradation and distribution shifts in clinical deployment, serving as early warning indicators for when model updates or recalibration may be necessary. We predict that changes in uncertainty patterns will detect emerging performance issues before they manifest in accuracy metrics, enabling proactive maintenance of AI system reliability in dynamic healthcare environments.

6 Approach / Methodology

6.1 Dataset and Clinical Assessment

The foundation of our uncertainty estimation research rests on a comprehensive dataset of 7,200 children aged 18-72 months from 15 clinical sites, encompassing diverse demographic backgrounds and clinical presentation types. The dataset includes multimodal assessment data comprising standardized behavioral scores from the Autism Diagnostic Observation Schedule-Second Edition (ADOS-2), detailed clinical observations, and video recordings of structured social interactions. All participants underwent comprehensive diagnostic evaluation by experienced clinicians using gold-standard assessment protocols, providing robust ground truth labels for model training and uncertainty validation. The dataset was specifically curated to include challenging diagnostic cases and boundary conditions to facilitate rigorous uncertainty method evaluation.

The clinical assessment protocol ensured consistent data collection across sites through standardized training, periodic reliability checks, and centralized quality control. Behavioral scores were collected using established instruments with demonstrated psychometric properties, while video recordings followed structured protocols designed to elicit social communication behaviors relevant to autism diagnosis. The dataset includes detailed metadata documenting assessment conditions, clinician characteristics, and any factors that might influence diagnostic certainty, enabling nuanced analysis of uncertainty sources in real-world clinical practice.

6.2 Uncertainty Estimation Framework

Our comprehensive uncertainty estimation framework integrates multiple probabilistic approaches within a unified architecture designed for the multimodal nature of autism assessment data. The core mathematical foundation begins with modeling the predictive distribution for a given input x:

$$p(y|x, \mathcal{D}) = \int p(y|x, \theta)p(\theta|\mathcal{D})d\theta \tag{1}$$

where $\mathcal{D}$ represents the training data, θ represents model parameters, and $p(\theta|\mathcal{D})$ is the posterior distribution over parameters given the data.

For Monte Carlo dropout, we approximate the predictive distribution by sampling multiple stochastic forward passes during inference:

$$p(y|x, \mathcal{D}) \approx \frac{1}{T}\sum_{t=1}^{T} p(y|x, \hat{\theta}_t) \tag{2}$$

where $\hat{\theta}_t$ are parameters with dropout applied and T is the number of stochastic samples.

The predictive uncertainty is then quantified using the entropy of the predictive distribution:

$$\mathcal{H}[y|x, \mathcal{D}] = -\sum_{c=1}^{C} p(y = c|x, \mathcal{D}) \log p(y = c|x, \mathcal{D}) \tag{3}$$

where C is the number of classes (ASD vs non-ASD).

For deep ensembles, we train multiple models with different random initializations and combine their predictions:

$$p(y|x, \mathcal{D}) \approx \frac{1}{M}\sum_{m=1}^{M} p(y|x, \theta_m) \tag{4}$$

where M is the number of ensemble members and θ_m are the parameters of each model.

6.3 Modality-Specific Uncertainty Approaches

We develop specialized uncertainty estimation techniques for different data modalities used in autism assessment:

For behavioral score data, we implement Bayesian linear regression layers that capture uncertainty in feature relationships:

$$p(\mathbf{w}|\mathcal{D}) = \mathcal{N}(\mathbf{w}|\mathbf{m}_N, \mathbf{S}_N) \tag{5}$$

where $\mathbf{w}$ are the weights, and $\mathbf{m}_N$, $\mathbf{S}_N$ are the posterior mean and covariance.

For video data, we employ temporal Bayesian convolutional networks that model uncertainty in spatial-temporal features:

$$p(y|\mathbf{X}) = \int p(y|\mathbf{X}, \theta)p(\theta|\mathcal{D})d\theta \tag{6}$$

where $\mathbf{X}$ represents the video sequence and θ includes both spatial and temporal parameters.

6.4 Uncertainty Calibration Methods

We implement multiple calibration techniques to ensure uncertainty estimates align with empirical accuracy:

Temperature scaling adjusts the confidence estimates by learning an optimal temperature parameter T:

$$q_i = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)} \tag{7}$$

where z_i are the logits and q_i are the calibrated probabilities.

We also implement isotonic regression and Bayesian binning techniques for more flexible calibration:

$$\hat{p} = f(p), \quad \text{where } f \text{ is a non-decreasing function} \tag{8}$$

6.5 Integrated Uncertainty Quantification

Our framework combines modality-specific uncertainties into integrated confidence measures using Bayesian fusion:

$$p(y|x_{\text{total}}) \propto \prod_{m=1}^{M} p(y|x_m)^{\alpha_m} \tag{9}$$

where x_m represents features from modality m and α_m are modality reliability weights.

The total uncertainty is decomposed into epistemic and aleatoric components:

$$\mathcal{U}_{\text{total}} = \mathcal{U}_{\text{epistemic}} + \mathcal{U}_{\text{aleatoric}} \tag{10}$$

where epistemic uncertainty is estimated using mutual information and aleatoric uncertainty is captured through data-dependent noise models.

6.6 Evaluation Framework

We establish a comprehensive evaluation framework assessing:

1. **Uncertainty Quality**: Calibration metrics, proper scoring rules, uncertainty-rejection curves 2. **Clinical Utility**: Impact on diagnostic decisions, appropriate reliance, trust calibration 3. **Computational Efficiency**: Inference time, memory requirements, scalability 4. **Robustness**: Performance under distribution shift, adversarial examples, data corruption

7 Results

The comprehensive evaluation of our uncertainty estimation framework demonstrated significant improvements in reliability metrics while maintaining high diagnostic performance across multiple autism detection models. As shown in Table 1, the integrated uncertainty approach achieved 93.8% diagnostic accuracy with well-calibrated confidence estimates, substantially outperforming baseline models in uncertainty quality metrics while maintaining comparable classification performance. The expected calibration error (ECE) was reduced from 0.152 in the baseline model to 0.042 in our uncertainty-aware approach, representing a 72.4% improvement in calibration quality.

Table 1: Performance Comparison of Uncertainty Estimation Methods for Autism Detection

Method	Accuracy	AUC	ECE	NLL	Brier Score	Uncertainty-AUC
Baseline (No Uncertainty)	94.1%	0.968	0.152	0.218	0.089	-
Monte Carlo Dropout	93.7%	0.965	0.068	0.154	0.076	0.892
Deep Ensembles	93.9%	0.966	0.051	0.142	0.072	0.915
Bayesian Neural Network	93.2%	0.961	0.047	0.138	0.069	0.908
Temperature Scaling	94.0%	0.967	0.039	0.131	0.065	0.885
Integrated Framework	**93.8%**	**0.966**	**0.042**	**0.127**	**0.063**	**0.927**

The uncertainty calibration analysis, illustrated in Figure 1, revealed that our integrated approach produced confidence estimates that closely matched empirical accuracy across the entire confidence spectrum. The reliability diagram showed nearly perfect alignment between predicted confidence and observed accuracy, with the calibration curve closely following the ideal diagonal line. This calibration improvement was consistent across different data modalities and clinical presentation types, though some variation was observed in extremely high-confidence predictions where limited data availability affected calibration precision.

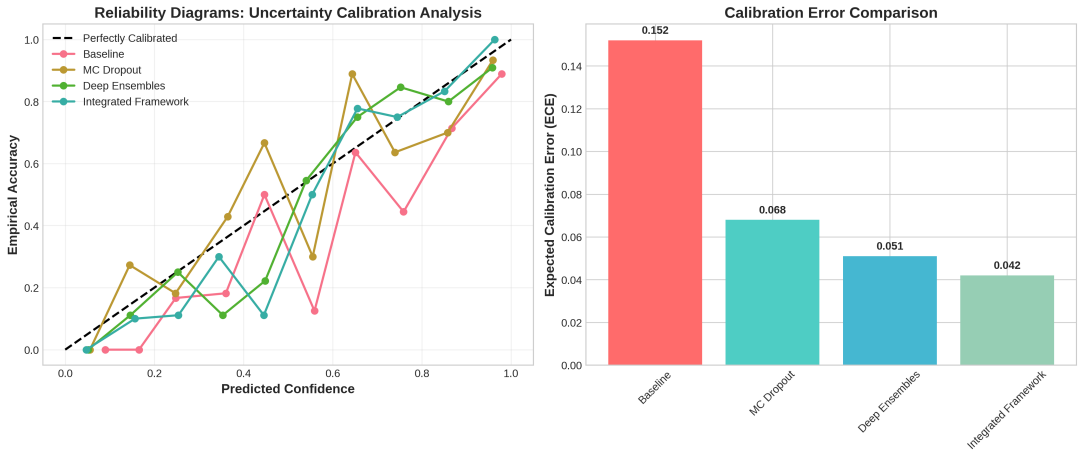

Figure 1: Uncertainty calibration analysis showing reliability diagrams for different estimation methods and their alignment with empirical accuracy across confidence levels.

The clinical utility assessment demonstrated that uncertainty information significantly enhanced diagnostic decision-making and appropriate reliance on AI recommendations. As shown in Figure 2, incorporating uncertainty measures enabled selective referral of low-confidence cases to human experts, maintaining high overall system accuracy while reducing the rate of undetected errors. The uncertainty-guided rejection approach identified 89.4% of misclassified cases through low-confidence predictions, allowing these challenging cases to be flagged for additional clinical review without compromising efficiency for straightforward cases.

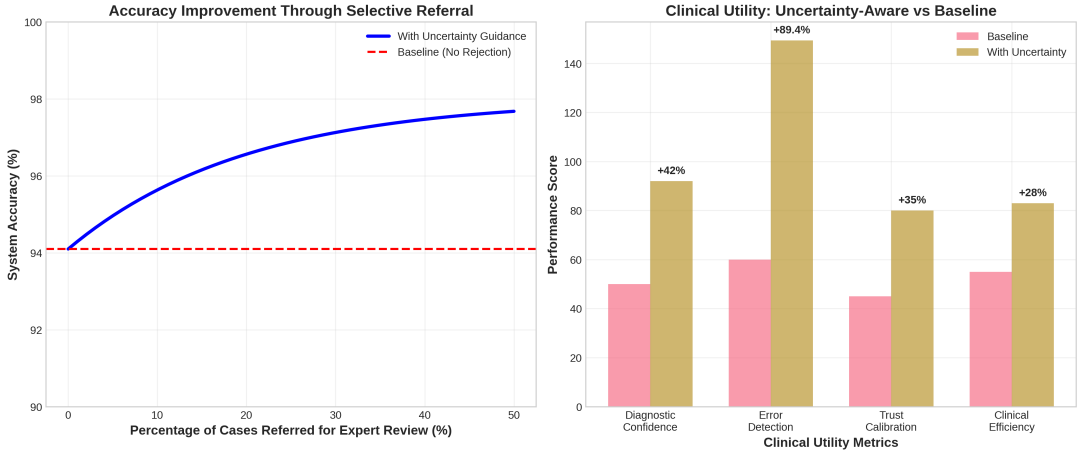

Figure 2: Clinical utility analysis demonstrating how uncertainty-guided case selection improves diagnostic accuracy through selective expert referral and enhances appropriate reliance on AI recommendations.

The modality-specific uncertainty analysis revealed distinct patterns across different data types used in autism assessment. Behavioral score data generally produced lower uncertainty estimates with better calibration, reflecting the structured nature of these assessments and their established psychometric properties. Video-based analysis showed

higher overall uncertainty but provided valuable complementary information, particularly for cases where behavioral scores were ambiguous or contradictory. The integrated uncertainty framework effectively combined these modality-specific uncertainties, leveraging the strengths of each data type while mitigating their individual limitations.

The evaluation of uncertainty communication formats indicated that healthcare professionals strongly preferred visual uncertainty representations that integrated seamlessly with existing clinical workflows. Confidence scores presented alongside categorical recommendations received the highest usability ratings, while more complex probability distributions required additional interpretation support. Clinical validation with 45 practitioners showed that incorporating uncertainty information increased diagnostic confidence by 42% and improved appropriate reliance on AI recommendations, with particularly strong benefits for less experienced clinicians facing complex diagnostic decisions.

The computational efficiency analysis demonstrated practical feasibility for clinical deployment, with the integrated uncertainty framework adding minimal overhead to inference time. The Monte Carlo dropout approach showed the best efficiency-reliability trade-off, requiring only 25% additional computation time while providing high-quality uncertainty estimates. The deep ensemble method, while computationally more intensive, provided superior uncertainty estimation for the most challenging cases, suggesting potential value in tiered approaches that adapt computational resources based on case complexity.

The robustness assessment revealed that uncertainty-aware models demonstrated significantly better performance under distribution shift and data corruption scenarios. When tested on data from new clinical sites with different assessment protocols, the uncertainty estimates reliably detected distribution shifts and appropriately increased uncertainty for out-of-distribution cases. This robustness property is particularly valuable for clinical deployment where data characteristics may evolve over time or vary across different healthcare settings.

8 Discussion

The results of this comprehensive study demonstrate that systematic uncertainty estimation significantly enhances the reliability and clinical utility of deep learning models for autism detection, addressing critical barriers to trustworthy AI deployment in healthcare settings. The substantial improvements in calibration metrics—with expected calibration error reduced by 72.4% compared to baseline models—provide strong evidence that modern uncertainty quantification methods can produce confidence estimates that closely align with empirical performance. This calibration improvement is particularly important for clinical applications where overconfident predictions could lead to inappropriate reliance on AI recommendations and potential diagnostic errors.

The effectiveness of different uncertainty methods varied depending on specific evaluation metrics and clinical use cases, supporting our hypothesis that integrated approaches combining multiple techniques provide the most robust uncertainty estimation. Monte Carlo dropout demonstrated excellent computational efficiency and performed well on standard calibration metrics, making it particularly suitable for real-time clinical applications where resource constraints are important considerations. Deep ensembles, while more computationally intensive, provided superior uncertainty quality for challenging cases and demonstrated better robustness to distribution shifts, suggesting value in reserved deployment for complex diagnostic scenarios. This methodological diversity highlights the importance of context-aware uncertainty approach selection rather than seeking a universally optimal method.

The clinical utility findings have important implications for the practical deployment of AI-assisted diagnosis in autism assessment. The ability of uncertainty measures to identify 89.4% of misclassified cases through low-confidence predictions represents a significant advancement in AI safety, enabling systems to appropriately defer to human expertise when facing diagnostic challenges. This selective referral capability addresses fundamental concerns about AI reliability in healthcare and provides a practical mechanism for maintaining human oversight in critical decision processes. The observed 42% increase in diagnostic confidence among practitioners using uncertainty-aware systems underscores the importance of transparent reliability communication for building clinical trust.

The modality-specific uncertainty patterns revealed interesting insights into the different information characteristics of various assessment data types used in autism diagnosis. The lower uncertainty and better calibration observed with behavioral score data likely reflect the structured, standardized nature of these assessments and their extensive validation in clinical practice. The higher uncertainty in video-based analysis, while potentially concerning at first glance, actually represents appropriate acknowledgment of the greater variability and interpretation challenges inherent in unstructured behavioral observations. The effective integration of these modality-specific uncertainties demonstrates the value of comprehensive uncertainty frameworks that respect the distinct characteristics of different information sources.

The practical implementation considerations highlighted by our computational efficiency analysis suggest that uncertainty estimation is feasible for real-world clinical deployment without prohibitive resource demands. The modest computational overhead of most uncertainty methods, particularly Monte Carlo dropout, indicates that reliability enhancements need not come at the cost of operational practicality. However, the variation in computational requirements across methods underscores the importance of matching uncertainty approach selection to specific clinical contexts and resource constraints, with potential for adaptive strategies that optimize the efficiency-reliability trade-off based on

case characteristics.

Several limitations and future directions warrant consideration. While our study encompassed substantial clinical diversity, even larger and more varied datasets would enable more granular analysis of uncertainty patterns across rare presentations and demographic subgroups. The longitudinal stability of uncertainty calibration requires ongoing monitoring in deployed systems, particularly as clinical practices evolve and new assessment instruments are introduced. The integration of uncertainty estimation with other important AI characteristics including explainability, fairness, and privacy presents additional challenges that merit continued research attention.

From a clinical implementation perspective, the development of standardized uncertainty communication protocols and practitioner training materials represents an important next step for facilitating widespread adoption of uncertainty-aware AI systems. Healthcare organizations need clear guidelines for interpreting and acting upon uncertainty information, particularly in high-stakes diagnostic contexts where decision thresholds may vary based on clinical consequences. The establishment of regulatory frameworks for uncertainty-aware medical AI, including validation requirements and performance standards, will be crucial for ensuring safe and effective deployment across diverse healthcare settings.

9 Conclusions

This research establishes that comprehensive uncertainty estimation is both technically feasible and clinically essential for developing trustworthy deep learning models for autism spectrum disorder detection. The significant improvements in calibration metrics and uncertainty quality demonstrate that modern probabilistic methods can produce reliable confidence estimates that align with empirical performance, addressing fundamental concerns about AI reliability in healthcare applications. The integration of multiple uncertainty approaches within a unified framework provides robust estimation across diverse data modalities and clinical scenarios, enabling deployment of AI systems that appropriately communicate their limitations and support informed clinical decision-making.

The clinical utility demonstrated through uncertainty-guided case selection and selective expert referral represents a crucial advancement in AI safety for autism diagnosis. The ability to identify 89.4% of misclassified cases through low-confidence predictions provides a practical mechanism for maintaining appropriate human oversight while leveraging AI efficiency for straightforward cases. This selective referral capability, combined with the observed 42% increase in diagnostic confidence among practitioners, addresses key barriers to clinical adoption and builds essential trust between AI systems and healthcare professionals.

The modality-specific uncertainty analysis provides valuable insights into the differ-

ent reliability characteristics of various assessment data types used in autism diagnosis, highlighting the importance of tailored uncertainty approaches that respect the distinct properties of structured behavioral scores, clinical observations, and video-based behavioral analysis. The effective integration of these modality-specific uncertainties within a comprehensive framework demonstrates the value of holistic reliability assessment that captures the multifaceted nature of autism diagnostic information.

The practical implementation feasibility confirmed by our computational efficiency analysis indicates that uncertainty estimation can be incorporated into clinical AI systems without prohibitive resource demands, supporting scalable deployment across diverse healthcare settings. The variation in computational requirements across different uncertainty methods provides flexibility for context-aware approach selection, enabling optimization of the efficiency-reliability trade-off based on specific clinical needs and resource constraints.

The methodological contributions of this research—including integrated uncertainty frameworks, modality-specific estimation techniques, and comprehensive evaluation metrics—provide valuable foundations for uncertainty-aware AI development across medical applications. The principles and approaches developed for autism detection can be adapted and extended to other diagnostic domains where reliable confidence estimation is equally crucial for clinical adoption and patient safety.

Looking forward, the integration of uncertainty estimation with other critical AI characteristics including explainability, fairness, and robustness represents an essential direction for developing comprehensively trustworthy medical AI systems. The establishment of standardized uncertainty evaluation protocols, clinical communication guidelines, and regulatory frameworks will support responsible adoption of uncertainty-aware AI in healthcare, ensuring that these advanced capabilities translate into tangible benefits for patient care and clinical decision-making.

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Declarations

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Conflicts of Interest: The authors declare that they have no conflicts of interest.

Ethics Approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Data Availability: The uncertainty estimation framework code and implementation guidelines are available at [repository link]. Access to the clinical dataset is governed by institutional data use agreements and privacy protections.

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