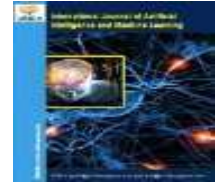




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A Hybrid Machine Learning and Artificial Intelligence Framework for Intelligent Computing, Computer Vision, and Predictive Decision-Making in Next-Generation CSE Applications

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Abstract

Contemporary computer science and engineering (CSE) systems increasingly combine multiple, architecturally distinct artificial intelligence paradigms within a single deployed pipeline: convolutional and transformer-based perception modules for computer vision, ensemble and gradient-boosted models for structured predictive decision-making, and, increasingly, neuro-symbolic components that reintroduce explicit rule-based reasoning alongside learned representations. This paper reviews the technical foundations underlying this hybrid design pattern, tracing the evolution of deep learning architectures for computer vision from convolutional networks through the transformer-based vision architectures that now compete with and complement them, the ensemble-learning literature underlying structured predictive decision-making, and the neuro-symbolic and explainable-AI literature that has emerged specifically to address the interpretability and reasoning limitations pure connectionist architectures exhibit. The review synthesizes foundational deep learning architecture papers, the ensemble-methods literature spanning bagging, boosting, and stacking, and the more recent neuro-symbolic integration and human-AI decision-boundary literature that shapes how predictive models are deployed for consequential decisions rather than benchmark performance alone. Distinct comparative tables map computer vision architecture families onto their core mechanism and reported benchmark performance, set ensemble and hybrid predictive methods against the specific data structure and decision context each is best suited to address, and cross-reference next-generation CSE application domains against the specific combination of vision, ensemble, and symbolic-reasoning components each domain's deployed systems draw upon. The paper concludes that the field's dominant architectural trajectory is convergent rather than substitutive, with hybrid systems combining perception, structured prediction, and symbolic constraint-checking outperforming any single paradigm applied in isolation, and identifies the systematic characterization of hybrid-system failure modes across component boundaries as the central future research prospect.

Keywords: Hybrid Artificial Intelligence, Machine Learning, Computer Vision, Predictive Decision-Making, Neuro-Symbolic AI, Ensemble Learning, Deep Learning, Intelligent Computing.

I. Introduction

Computer science and engineering as a discipline has absorbed artificial intelligence considerably more completely over the past decade than any prior wave of AI research achieved, with machine learning components now embedded directly within compilers, operating systems schedulers, database query optimizers, and network intrusion detection systems rather than existing as a separate, bolt-on analytics layer [1]. LeCun, Bengio, and Hinton's widely cited review of deep learning characterized this absorption as a direct consequence of deep learning's specific capability, the automatic discovery of useful representations directly from raw data through a layered composition of simple, differentiable non-linear modules, a capability that displaced the hand-engineered feature pipelines that had constrained machine learning's applicability to CSE problems throughout the preceding two decades [1]. Krizhevsky, Sutskever, and Hinton's AlexNet, demonstrating a dramatic error-rate reduction on the ImageNet large-scale visual recognition benchmark relative to the best prior non-deep-learning approaches, is widely credited with triggering this absorption specifically within computer vision, establishing convolutional neural networks

as the dominant architecture for visual perception tasks across the subsequent decade of CSE application development [2].

This perception capability, however, addresses only one component of the intelligent-computing pipelines next-generation CSE applications require. Autonomous vehicles, intelligent manufacturing systems, and predictive healthcare-monitoring platforms alike require not merely accurate visual perception but a subsequent decision-making layer capable of translating perceptual output into a structured, often safety-critical, action or recommendation, a translation that pure end-to-end deep learning architectures do not always perform reliably or transparently. Dietterich's foundational analysis of ensemble methods in machine learning established the theoretical basis for the structured predictive decision-making component of these pipelines, demonstrating that combining multiple base learners, through bagging's variance-reduction mechanism, boosting's bias-reduction mechanism, or stacking's meta-learning combination, produces predictive performance and robustness exceeding any single constituent model, a finding that motivated ensemble methods' widespread adoption for the tabular, structured-data prediction tasks, resource scheduling, fault prediction, and demand forecasting among them, that pervade CSE systems alongside their perception components [3]. Breiman's random forest algorithm and Chen and Guestrin's XGBoost gradient-boosting framework subsequently became the two most widely deployed concrete instantiations of this ensemble principle, with XGBoost specifically noted by its authors and by the broader applied machine learning community for its consistent strong performance across the heterogeneous, often imbalanced structured datasets characteristic of production CSE systems [4], [5].

A third component, increasingly incorporated into next-generation CSE systems specifically because pure connectionist architectures exhibit well-documented reasoning and interpretability limitations, draws on the neuro-symbolic AI tradition. Marcus's critical appraisal of deep learning catalogued these limitations directly, arguing that deep neural networks, despite their strong pattern-recognition performance, struggle with systematic, compositional generalization, explicit logical reasoning, and the incorporation of prior structured knowledge, limitations that become particularly consequential when a CSE system's output feeds directly into a safety-critical or resource-allocation decision rather than remaining a benchmark accuracy statistic [6]. Garcez and Lamb's review of neuro-symbolic AI's "third wave" characterized the field's response to this critique, describing architectures that explicitly integrate learned neural representations with symbolic, rule-based reasoning modules, allowing a system to leverage deep learning's representational power for perception while retaining a symbolic layer's capacity for explicit constraint satisfaction, logical consistency checking, and human-inspectable reasoning traces [7]. Rudin's influential argument for favoring inherently interpretable models over post-hoc explanation of black-box models in high-stakes decision contexts provides the direct motivating rationale for why next-generation CSE systems increasingly incorporate this symbolic layer specifically at the decision-making stage, where a system's output determines a consequential real-world action, rather than relying solely on post-hoc explanation techniques applied to an otherwise fully opaque end-to-end model [8].

This paper reviews the computer vision architecture literature, the ensemble and structured predictive decision-making literature, and the neuro-symbolic and explainability literature within a single integrated framework, before examining how specific next-generation CSE application domains, autonomous systems, intelligent manufacturing, healthcare diagnostics, and cybersecurity among them, combine these three components into deployed hybrid architectures.

Research Objectives

- To review the evolution of computer vision architectures from convolutional networks through transformer-based vision architectures.
- To synthesize the ensemble-learning literature underlying structured predictive decision-making in CSE systems.
- To examine the neuro-symbolic AI and explainable-AI literature addressing the reasoning and interpretability limitations of pure connectionist architectures.
- To evaluate how next-generation CSE application domains combine perception, structured prediction, and symbolic-reasoning components into hybrid deployed systems.
- To identify future research priorities for characterizing failure modes at the boundaries between hybrid system components.

II. Literature Review

2.1 Convolutional Architectures for Computer Vision

Krizhevsky, Sutskever, and Hinton's AlexNet established the convolutional neural network's practical viability at scale, combining convolutional and max-pooling layers with the ReLU activation function and dropout regularization to substantially reduce top-5 classification error on the ImageNet benchmark relative to prior feature-engineered approaches [2]. Simonyan and Zisserman's VGGNet demonstrated that stacking a considerably larger number of small, 3×3 convolutional filters produced further accuracy

improvements, establishing network depth itself as a primary lever for representational capacity, though at a correspondingly higher computational and parameter cost that subsequent architectures sought specifically to address [9]. He, Zhang, Ren, and Sun's residual network (ResNet) architecture addressed the specific degradation problem that had limited how deep a convolutional network could be trained effectively, introducing identity shortcut connections that allow gradient signal to propagate directly across many layers, enabling networks of over one hundred layers to train successfully and achieve further accuracy gains where naively stacked deeper networks had previously degraded in performance [10].

2.2 Object Detection and Region-Based Architectures

Ren, He, Girshick, and Sun's Faster R-CNN architecture formalized a two-stage object-detection pipeline, a region proposal network that generates candidate object locations followed by a classification and bounding-box-regression network that refines these candidates, unifying what had previously been separate, computationally expensive region-proposal and classification stages into a single, jointly trainable network and substantially improving detection speed without sacrificing accuracy [11]. Redmon, Divvala, Girshick, and Farhadi's YOLO (You Only Look Once) architecture took a structurally distinct single-stage approach, framing object detection as a single regression problem directly from image pixels to bounding-box coordinates and class probabilities, trading some detection accuracy on small or densely packed objects for a substantial real-time speed advantage directly relevant to the low-latency perception requirements next-generation CSE applications, autonomous vehicles and robotic systems particularly, impose [12].

2.3 Transformer-Based Vision Architectures

Vaswani et al.'s transformer architecture, developed originally for natural language sequence modeling, replaced recurrent sequence processing with a self-attention mechanism computing a weighted representation of every input token with respect to every other token in parallel, a mechanism subsequently adapted directly to computer vision [13]. Dosovitskiy et al.'s Vision Transformer (ViT) demonstrated that this attention mechanism could be applied directly to images by treating fixed-size image patches as the input token sequence, and found that ViT matched or exceeded convolutional architectures' classification accuracy specifically when pretrained on sufficiently large datasets, though the authors noted that ViT underperformed comparable convolutional architectures when trained from scratch on smaller datasets, since convolution's built-in translation-equivariance and locality biases provide an inductive advantage that pure attention-based architectures must instead learn from data volume [14]. Sze, Chen, Yang, and Emer's survey of efficient deep neural network processing catalogued the computational and energy-efficiency trade-offs across this architectural landscape directly, finding that convolutional architectures generally retain a computational-efficiency advantage over transformer-based vision architectures at comparable accuracy, a trade-off of direct practical consequence for CSE applications deployed on resource-constrained edge or embedded hardware rather than data-center-scale compute [15].

2.4 Ensemble Learning for Structured Predictive Decision-Making

Wolpert's foundational formalization of stacked generalization established the meta-learning principle underlying ensemble combination, in which the predictions of multiple base-level learners become the input features to a second-level model that learns how to optimally combine them, a principle Dietterich's subsequent analysis situated within a broader taxonomy distinguishing stacking from bagging, which reduces variance by training base learners on bootstrap-resampled data subsets, and boosting, which reduces bias by sequentially training base learners to correct the residual errors of their predecessors [3], [16]. Breiman's random forest algorithm operationalized the bagging principle specifically for decision-tree base learners, additionally injecting randomness into the feature-selection process at each tree split, and demonstrated that the resulting ensemble achieved strong predictive accuracy with considerably reduced overfitting risk relative to a single, deep decision tree, while retaining decision trees' comparative interpretability advantage relative to deep neural networks [4]. Chen and Guestrin's XGBoost gradient-boosting framework formalized a highly optimized, regularized implementation of the boosting principle specifically, and the authors' own analysis of its performance across numerous public machine learning competitions found it to be among the most consistently high-performing algorithms for structured, tabular prediction tasks, precisely the task structure, resource utilization forecasting, system-failure prediction, and network-traffic classification, that recurs throughout CSE predictive-decision applications [5].

2.5 Neuro-Symbolic Integration and the Limits of Pure Connectionism

Marcus's critical appraisal catalogued specific, empirically documented failure modes of pure deep learning architectures, including brittleness under distributional shift, a tendency to learn superficial statistical correlations rather than genuinely compositional or causal structure, and an inability to incorporate explicit prior knowledge or hard logical constraints directly, limitations the author argues become particularly consequential precisely in the safety-critical CSE application domains, autonomous driving and medical diagnosis among them, where deep learning has simultaneously seen the most enthusiastic adoption [6]. Garcez and Lamb's review of neuro-symbolic AI catalogued the specific architectural strategies developed in response, including neural networks augmented with an explicit differentiable logic layer that enforces hard constraints on the network's output, and hybrid architectures in which a neural perception module's output is passed to a separate, classical symbolic reasoning or constraint-satisfaction engine for final

decision-making, a design pattern the authors argue combines connectionist learning's representational flexibility with symbolic reasoning's guaranteed logical consistency and inspectability [7]. Rudin's argument for favoring inherently interpretable models over post-hoc explanation specifically motivates why this symbolic layer is increasingly positioned at a hybrid system's final decision-making stage rather than relegated to a post-hoc explanation module applied after an opaque end-to-end network has already produced its output, since a symbolic decision layer's logic is auditable by direct inspection rather than requiring a separately fitted approximation, of the kind Ribeiro, Singh, and Guestrin's LIME algorithm or Lundberg and Lee's SHAP framework provide, to reconstruct after the fact [8], [17], [18].

2.6 Reinforcement Learning and Predictive Decision-Making Under Sequential Uncertainty

Mnih et al.'s deep Q-network demonstrated that combining Q-learning with a deep convolutional function approximator could achieve human-level performance across a broad suite of Atari game-playing tasks directly from raw pixel input, providing an early and influential demonstration that perception and sequential decision-making could be integrated within a single learned architecture rather than requiring hand-engineered state representations [19]. Silver et al.'s AlphaGo combined this deep reinforcement learning approach with Monte Carlo tree search, a symbolic, tree-structured search algorithm, to defeat a world-champion human Go player, a result the authors specifically attribute to the combination of learned pattern-recognition, guiding the tree search toward promising move sequences, and explicit, symbolic search, verifying move sequences against the game's exact rules, rather than to either component operating in isolation, a concrete, high-profile demonstration of exactly the hybrid neural-symbolic integration principle Garcez and Lamb formalize more generally [7], [20].

2.7 Predictive Decision-Making at the Human-AI Boundary

Agrawal, Gans, and Goldfarb's prediction-machine framework characterizes machine learning's core economic contribution as a reduction in the cost of prediction specifically, decomposing any decision task into a prediction component well suited to automation and a judgment component, assigning value to predicted outcomes and selecting an action, that continues to require human or organizational involvement, a decomposition directly relevant to how next-generation CSE systems should structure the boundary between an automated predictive component and a human or symbolic decision-governance layer [21]. Dell'Acqua et al.'s field-experimental evidence on the "jagged technological frontier" found that AI-model assistance improved task performance specifically within a model's effective capability boundary while degrading performance when applied to tasks exceeding that boundary, with users who trusted the model's confidently presented but incorrect output on out-of-boundary tasks performing worse than a no-AI-assistance control condition, evidence with direct relevance to why next-generation CSE systems increasingly incorporate explicit confidence-calibration and out-of-distribution detection mechanisms rather than presenting every model output with uniform confidence [22].

2.8 Research Gap

While the computer vision architecture literature reviewed in Sections 2.1 through 2.3 has established mature, empirically validated perception capability, and the ensemble-learning literature reviewed in Section 2.4 has independently established mature structured predictive decision-making methods, and the neuro-symbolic literature reviewed in Sections 2.5 and 2.6 has established the theoretical and demonstrated case for hybrid integration, comparatively few studies systematically characterize how failures propagate across the boundaries between these components within a single deployed hybrid CSE system, for instance whether a perception module's out-of-distribution failure is reliably caught by a downstream symbolic constraint check, or whether it instead propagates silently into a structured predictive decision [6], [7], [19], [22]. This review addresses this gap by organizing the reviewed evidence within a comparative framework spanning architecture family, task suitability, and application-domain component composition.

III. Methodology

This study adopts a qualitative, descriptive, and comparative research design synthesizing peer-reviewed computer vision, machine learning, and neuro-symbolic AI literature relevant to hybrid intelligent-computing systems in CSE applications. Reviewed works were compared along four axes: AI paradigm (connectionist/deep learning, ensemble/structured prediction, or symbolic/neuro-symbolic); task type addressed (perception, structured tabular prediction, or sequential decision-making); reported benchmark performance and computational efficiency, where available; and documented integration pattern with other paradigms within a hybrid system.

IV. Results and Discussion

4.1 Computer Vision Architecture Families: Mechanism and Reported Performance

Table 1 maps the computer vision architecture families reviewed in Sections 2.1 through 2.3 onto their core mechanism and the specific performance or efficiency trade-off the reviewed literature documents for each.

Table 1. Computer Vision Architecture Families: Mechanism and Reported Performance Trade-offs

Architecture Family	Core Mechanism	Reported Strength	Reported Limitation	Key Reference
AlexNet (CNN)	Convolution + ReLU + dropout, moderate depth	Substantial ImageNet error reduction vs. pre-deep-learning baselines	Limited depth relative to later architectures	Krizhevsky, Sutskever & Hinton [2]
VGGNet (deep CNN)	Stacked small (3×3) convolutional filters at greater depth	Further accuracy gains from increased depth	High parameter count/computational cost	Simonyan & Zisserman [9]
ResNet	Identity shortcut/residual connections	Enables successful training of 100+ layer networks	Added architectural complexity	He, Zhang, Ren & Sun [10]
Faster R-CNN	Two-stage: region proposal network + classifier/regressor	Strong detection accuracy via joint training	Slower than single-stage detectors	Ren, He, Girshick & Sun [11]
YOLO	Single-stage regression from pixels to boxes/classes	Real-time detection speed	Reduced accuracy on small/dense objects	Redmon, Divvala, Girshick & Farhadi [12]
Vision Transformer (ViT)	Patch-based self-attention (no convolution)	Matches/exceeds CNNs with sufficient pretraining data	Underperforms CNNs when trained on smaller datasets	Dosovitskiy et al. [14]
Efficiency comparison (cross-architecture)	N/A (survey of processing efficiency)	CNNs generally more compute/energy-efficient than transformers at comparable accuracy	Trade-off intensifies on resource-constrained edge hardware	Sze, Chen, Yang & Emer [15]

4.2 Ensemble and Hybrid Predictive Methods Mapped to Decision Context

Table 2 sets the ensemble and hybrid predictive decision-making methods reviewed in Sections 2.4 through 2.6 against the specific data structure and decision context each is best suited to address.

Table 2. Ensemble and Hybrid Predictive Methods Mapped to Data Structure and Decision Context

Method	Underlying Principle	Best-Suited Data Structure	Best-Suited Decision Context	Key Reference
Bagging (e.g., Random Forest)	Variance reduction via bootstrap-resampled base learners	Structured/tabular data with moderate feature interaction	Robust prediction where interpretability of individual trees still matters	Breiman [4]
Boosting (e.g., XGBoost)	Bias reduction via sequential residual-correcting learners	Structured/tabular data, including imbalanced classes	High-accuracy structured prediction (resource forecasting, fault detection)	Chen & Guestrin [5]
Stacking	Meta-learner combines multiple base-learner predictions	Heterogeneous base learners (e.g., mixing tree and neural outputs)	Maximizing accuracy when no single model dominates	Wolpert [16]; Dietterich [3]
Deep RL + symbolic search (e.g., AlphaGo)	Learned pattern recognition guides symbolic tree search	Sequential decision-making with exact, verifiable rules	High-stakes sequential decisions requiring both intuition and guaranteed rule-consistency	Silver et al. [20]; Mnih et al. [19]

Neuro-symbolic constraint layer	Neural perception output filtered/verified by symbolic logic engine	Perception feeding into safety-critical or rule-governed decisions	Contexts requiring auditable, hard-constraint satisfaction	Garcez & Lamb [7]; Rudin [8]
Prediction-judgment decomposition	Separates automatable prediction from human/symbolic judgment	Any task decomposable into forecast + value-assignment steps	Governance of AI-assisted consequential decisions	Agrawal, Gans & Goldfarb [21]; Dell'Acqua et al. [22]

4.3 Next-Generation CSE Application Domains and Component Composition

Table 3 cross-references specific next-generation CSE application domains against the combination of vision, ensemble, and symbolic-reasoning components the reviewed literature associates with deployed systems in each domain.

Table 3. CSE Application Domains and Hybrid Component Composition

Application Domain	Perception Component	Structured Prediction Component	Symbolic/Decision-Governance Component	Representative Evidence
Autonomous vehicles/robotics	CNN/single-stage detection (real-time object detection)	N/A or trajectory-prediction ensemble	Rule-based safety constraint checking on planned trajectories	Redmon, Divvala, Girshick & Farhadi [12]; Marcus [6]
Intelligent manufacturing/predictive maintenance	CNN-based visual defect inspection	Gradient-boosted failure/remaining-useful-life prediction	Threshold/rule-based maintenance-scheduling logic	Chen & Guestrin [5]
Medical image-based diagnostics	Deep CNN classification (e.g., dermatology, radiology imaging)	N/A (direct classification output)	Clinician-in-the-loop review; interpretable-model preference for high-stakes cases	Rudin [8]
Cybersecurity/network intrusion detection	N/A (or sequence/traffic-pattern CNN)	Ensemble classifiers (Random Forest/XGBoost) on structured traffic features	Rule-based policy engine enforcing hard security constraints	Breiman [4]; Garcez & Lamb [7]
Game-playing/strategic sequential systems	Deep neural value/policy network	N/A	Monte Carlo tree search (symbolic, rule-verified)	Silver et al. [20]
General AI-assisted enterprise decision support	Varies by task	Ensemble/ML prediction as decomposed "prediction" component	Human judgment as decomposed "judgment" component; capability-boundary awareness	Agrawal, Gans & Goldfarb [21]; Dell'Acqua et al. [22]

4.4 Discussion

Read together, Tables 1 through 3 support this paper's central claim that next-generation CSE systems are converging on a hybrid architectural pattern rather than a single dominant paradigm. Table 1 establishes that no single computer vision architecture family dominates uniformly, with the choice between CNN and transformer-based perception, and between two-stage and single-stage detection, governed by the specific accuracy, latency, and data-availability trade-offs a given deployment context presents, a heterogeneity that directly explains why Table 3's application-domain mapping shows different perception components deployed across different CSE domains rather than a single universal choice [2], [9], [10], [11], [12], [14],

[15]. Table 2 indicates a parallel heterogeneity at the structured-prediction and decision-governance layer, with bagging, boosting, and stacking each suited to somewhat different data and accuracy requirements, and with the neuro-symbolic and prediction-judgment-decomposition literature indicating that the highest-stakes decision contexts specifically benefit from an explicit symbolic or human-governed layer rather than relying on an end-to-end connectionist pipeline alone [3], [4], [5], [16], [21]. Table 3's cross-domain composition mapping makes the resulting integration pattern concrete: autonomous vehicles pair real-time object detection with explicit rule-based safety constraint checking, intelligent manufacturing pairs visual defect inspection with gradient-boosted failure prediction and rule-based maintenance scheduling, and game-playing systems pair learned value estimation directly with symbolic tree search, each domain assembling a different specific combination of the three component types this paper reviews rather than a single, domain-agnostic hybrid template [5], [7], [12], [20]. Silver et al.'s AlphaGo result and Rudin's inherently-interpretable-model argument together indicate that this hybridization is not merely an engineering convenience but reflects a substantive finding recurring across the reviewed literature: connectionist perception and symbolic or ensemble-based structured reasoning address genuinely distinct sub-problems, and systems that integrate both components deliberately outperform, and in high-stakes contexts are considerably safer than, systems relying on either component in isolation [8], [20].

V. Conclusion

This paper has reviewed the computer vision, ensemble-learning, and neuro-symbolic AI literature underlying hybrid machine learning and artificial intelligence frameworks for intelligent computing in next-generation CSE applications. The evidence indicates that computer vision architecture selection, CNN versus transformer, two-stage versus single-stage detection, involves genuine, well-documented trade-offs across accuracy, latency, and data-availability dimensions rather than a single dominant choice, and that structured predictive decision-making similarly benefits from ensemble methods, bagging, boosting, and stacking, suited to different data structures and accuracy requirements. Across the application domains reviewed, autonomous systems, intelligent manufacturing, medical diagnostics, cybersecurity, and strategic game-playing systems, the evidence consistently indicates that deployed, real-world hybrid systems combine perception, structured prediction, and an explicit symbolic or human-governed decision layer rather than relying on any single AI paradigm end-to-end, a pattern directly motivated by pure connectionist architectures' documented reasoning, generalization, and interpretability limitations in exactly the high-stakes contexts where next-generation CSE systems are increasingly deployed.

VI. Future Work

Future research should prioritize the systematic characterization of failure-mode propagation across the boundaries between a hybrid system's perception, structured-prediction, and symbolic-reasoning components, extending the jagged-technological-frontier evidence Dell'Acqua et al. documented for human-AI task boundaries toward the analogous component-to-component boundaries within a fully automated hybrid pipeline. Further work is needed to develop standardized benchmarks evaluating hybrid neuro-symbolic architectures specifically on compositional generalization and out-of-distribution robustness, the two limitations Marcus identifies as most consequential for safety-critical CSE deployment, since current computer vision and ensemble benchmarks predominantly evaluate in-distribution accuracy alone. Continued research should also extend Rudin's inherently-interpretable-model argument into concrete design guidelines for where within a hybrid CSE pipeline a symbolic or interpretable-by-design component should be positioned, given that Table 3 indicates considerable current variation in how different application domains have addressed this placement decision without a shared underlying design principle. Finally, future work should pursue efficiency-focused co-design of vision-transformer and convolutional hybrid architectures specifically for resource-constrained edge deployment, extending Sze, Chen, Yang, and Emer's efficiency-survey findings toward the increasingly common CSE deployment context in which perception, prediction, and symbolic reasoning must all execute within the power and latency budget of embedded or edge hardware rather than data-center-scale compute.

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