IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 9, September 2026

DOI: 10.17148/IJARCCE.2026.15911

Adaptive Ensemble Machine Learning Framework for Robust Prediction, Classification, and Intelligent Decision Support Across Heterogeneous Data Domains

M. Sasikumar[1], Addepalli Keerthika[2], N Saranya[3]

Assistant Professor (SG), Department of Computer Science and Design, School of Computing,

Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, Tamil Nadu,

India – 600062[1]

UG Scholar, Department of Computer Science and Design, School of Computing, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, Tamilnadu, India – 600062[2,3]

Abstract: The increasing diversity and complexity of data across different application domains create significant challenges for conventional machine learning models in achieving robust prediction, classification, and intelligent decision support. This paper proposes an Adaptive Heterogeneous Dynamic Ensemble for Intelligent Decision Support (AHDE-DS) framework that integrates multiple heterogeneous machine learning and deep learning models within a unified adaptive architecture. The framework performs data preprocessing and feature representation, followed by parallel learning using complementary classifiers. A dynamic competence evaluation mechanism assesses each learner according to predictive performance, local competence, confidence, and uncertainty. Based on these measures, adaptive weights are assigned to the most competent models, and their outputs are fused through a stacking-based meta-learning mechanism. The final prediction is further processed by a confidence-aware decision-support layer. Experimental evaluation demonstrates that AHDE-DS achieves 98.73% accuracy, 98.61% precision, 98.54% recall, and 98.57% F1-score, outperforming the considered existing ensemble approaches. The results demonstrate the framework's effectiveness, adaptability, and robustness for heterogeneous data-driven intelligent applications.

Keywords: Adaptive Ensemble Learning, Heterogeneous Data, Dynamic Ensemble Selection, Machine Learning, Deep Learning, Stacking, Adaptive Weighting, Robust Prediction, Classification, Intelligent Decision Support

I. INTRODUCTION

The rapid proliferation of digital technologies has resulted in the generation of massive volumes of heterogeneous data across healthcare, agriculture, environmental monitoring, finance, cybersecurity, e-commerce, education, and social media. Such data differ substantially in structure, dimensionality, quality, temporal characteristics, and semantic representation. Consequently, developing machine learning models that can provide reliable prediction, accurate classification, and intelligent decision support across diverse application domains has become an important research challenge. Traditional single-model approaches may perform effectively under specific data conditions but can experience reduced generalisation when exposed to noisy, imbalanced, nonlinear, multimodal, or dynamically changing datasets. Ensemble machine learning provides a promising solution by combining the complementary strengths of multiple learning algorithms to improve predictive stability, robustness, and generalisation [1], [2].

Recent research demonstrates the effectiveness of ensemble and hybrid learning strategies in complex classification problems. In agricultural applications, ensemble-based deep learning has been explored for disease classification using spectral imagery, where the integration of multiple learning representations can improve the identification of visually complex disease patterns [1]. Similarly, temporal prediction research has demonstrated that combining attention mechanisms with machine learning and deep learning models can effectively capture important temporal and feature-level dependencies in multivariate environmental data [2]. These developments indicate that combining diverse learners can provide improved representation capabilities compared with conventional standalone models.

The importance of adaptive machine learning is further evident in forecasting applications involving highly dynamic data. Agricultural commodity price prediction, for example, requires models capable of learning nonlinear temporal

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 9, September 2026

DOI: 10.17148/IJARCCE.2026.15911

relationships and responding to changing market conditions [3]. Such applications demonstrate the need for predictive frameworks that can accommodate temporal variability while maintaining reliable forecasting performance. In healthcare, machine learning has increasingly been applied to predictive analytics and intelligent healthcare systems, where accurate classification and prediction can assist in identifying patterns and supporting data-driven decisions [4]. These applications highlight the importance of robust models capable of processing heterogeneous information while producing dependable outputs.

Machine learning has also demonstrated significant potential for extracting knowledge from unstructured and high-dimensional data. Sentiment analysis and opinion mining can transform large-scale social-media information into structured insights for understanding user opinions and behavioral trends [5]. In cybersecurity and public-safety applications, AI-driven analytics can process diverse security-related information to identify threats, recognize abnormal patterns, and support timely decision-making [6]. Similarly, intelligent emotion-recognition systems demonstrate the potential of machine learning to integrate complex information for personalized and context-aware decision support [7]. In e-commerce, machine-learning-based recommendation systems use learned patterns from users and products to generate personalized suggestions, demonstrating how predictive models can be transformed into actionable decisions [8].

Despite these advances, existing approaches are generally developed for individual application domains and often depend on fixed model configurations. A significant research gap therefore exists in developing a unified framework capable of dynamically selecting, weighting, and integrating heterogeneous machine learning models according to the characteristics of the input data and prediction task. Addressing this gap requires an adaptive ensemble architecture capable of exploiting model diversity while reducing the limitations of individual learners.

The proposed framework integrates diverse learning algorithms through adaptive model selection, feature-level learning, ensemble fusion, confidence-aware prediction, and decision-generation mechanisms. By dynamically exploiting complementary model capabilities, the framework aims to improve accuracy, robustness, generalisation, and reliability across heterogeneous datasets. The resulting architecture provides a flexible foundation for developing intelligent systems capable of addressing prediction, classification, and decision-support requirements across multiple real-world domains.

II. LITERATURE SURVEY

The development of robust machine learning systems has increasingly shifted from single-model prediction toward ensemble and hybrid learning architectures. Ensemble learning improves predictive reliability by combining multiple models that capture different characteristics of the underlying data. A comprehensive review of ensemble learning established that model diversity, aggregation strategies, and appropriate ensemble construction are fundamental to improving predictive performance across different machine learning tasks [9]. Stacked generalization has subsequently become an important approach for heterogeneous ensemble construction because it allows predictions from different base learners to be integrated through a higher-level meta-model [10]. This approach is particularly relevant to heterogeneous data environments, where individual algorithms may capture different relationships within the same dataset.

The challenge of heterogeneous data has also motivated the development of dynamic ensemble selection mechanisms. Conventional ensembles generally apply the same combination of classifiers to every input instance, whereas dynamic approaches select models according to their local competence. Research on dynamic ensemble selection for heterogeneous data demonstrated that data originating from different sources can be independently modeled and subsequently combined through decision-level fusion, reducing the need for direct feature-level integration [11]. This concept is highly relevant to the proposed framework because heterogeneous datasets may contain different feature structures, distributions, and representations. Dynamic selection can therefore enable the framework to identify the most appropriate predictive models according to the characteristics of individual observations.

Another important challenge is class imbalance, which can significantly influence the reliability of classification systems. Dynamic ensemble selection has been investigated specifically for multiclass imbalanced datasets, where classifier competence is evaluated according to the characteristics of local neighborhoods and underrepresented classes [12]. Such approaches demonstrate that adaptive classifier selection can improve classification performance in situations where conventional static ensembles may be biased toward majority classes. This provides an important foundation for developing robust decision-support systems in domains where minority cases are particularly important.

The application of ensemble learning to high-dimensional datasets has further demonstrated the importance of appropriate base-classifier selection. Research on stacked generalization for high-dimensional data indicates that the number and type

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 15, Issue 9, September 2026

DOI: 10.17148/IJARCCE.2026.15911

of classifiers used at the first level of a stacking architecture can substantially influence the final performance [13]. Consequently, simply increasing the number of models in an ensemble does not necessarily guarantee improved prediction. Effective ensemble design requires consideration of model complementarity, diversity, predictive competence, and computational efficiency.

Recent research has extended ensemble learning toward deep learning and multimodal intelligent systems. Comprehensive investigations of ensemble deep learning have emphasized the effectiveness of combining complementary representations through mechanisms such as voting, averaging, stacking, and weighted fusion [14]. These approaches provide a foundation for integrating conventional machine learning models with deep neural architectures, particularly when different models extract complementary information from complex datasets.

Within application-specific research, machine-learning-based website content categorization demonstrates the applicability of classification algorithms to large-scale web information, where diverse textual and semantic characteristics must be transformed into useful categories [15]. Similarly, intelligent learning-assistant systems have incorporated automated question generation, evaluation, assessment, and recursive testing to identify learner weaknesses and support personalized improvement [16]. These studies demonstrate the potential of machine learning to move beyond prediction toward continuous assessment and intelligent decision support.

Healthcare represents another important heterogeneous-data application. Machine-learning-based intelligent frameworks have been developed for intracranial tumor recognition, demonstrating how automated image analysis can support complex diagnostic tasks [17]. Research on AI-enabled radiology has similarly highlighted the increasing role of machine learning in medical-image segmentation, detection, and diagnosis [18]. Such applications require high reliability because prediction errors may directly affect subsequent decision-making. Therefore, ensemble architectures that combine complementary models can provide a useful mechanism for improving robustness.

Machine learning has also been applied to educational performance analysis, where predictive models are used to identify learning patterns and support improvement strategies [19]. In e-commerce, product suggestion systems demonstrate how predictive models can transform historical user–product interactions into personalized recommendations [20]. These applications emphasize that an intelligent machine learning framework should not be limited to classification or prediction alone but should also convert model outputs into actionable decisions.

Distributed and real-time environments introduce additional requirements for robust prediction. Research on enhanced packet-delivery protocols for 5G-assisted wireless sensor networks demonstrates the importance of intelligent models operating under dynamic communication and resource constraints [21]. Such environments can generate heterogeneous, continuously changing data and therefore require adaptive learning mechanisms capable of responding to changing conditions.

Recent work has also explored AI-driven database optimisation, demonstrating how machine learning can support intelligent data-management decisions [22]. Similarly, AI-based security-threat analytics emphasises the use of machine learning for identifying complex threat patterns and supporting public-safety decisions [23]. These applications reinforce the need for frameworks that can integrate diverse predictive models rather than depending on a single algorithm.

Overall, the reviewed literature demonstrates significant progress in ensemble learning, dynamic classifier selection, deep learning, predictive analytics, and intelligent decision support. However, most existing studies remain focused on individual application domains, specific data modalities, or particular ensemble mechanisms. A broader research gap remains in developing a unified adaptive architecture that can dynamically select and combine heterogeneous models across prediction, classification, and decision-support tasks. The proposed framework addresses this gap by integrating heterogeneous learners, adaptive weighting, model-competence evaluation, ensemble fusion, and decision-generation mechanisms within a common architecture. Such an approach can provide greater robustness and flexibility when the framework is transferred across heterogeneous

III. EXISTING SYSTEM

A. Existing System 1: Static Heterogeneous Ensemble Learning

The first existing system is a heterogeneous ensemble learning system based on stacked generalization. In this approach, multiple machine learning algorithms are trained independently on the same dataset, and their outputs are subsequently provided to a meta-classifier for generating the final prediction. Different base learners can capture different relationships within the data, thereby improving predictive performance compared with an individual classifier. Heterogeneous

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 15, Issue 9, September 2026

DOI: 10.17148/IJARCCE.2026.15911

stacking has been specifically investigated as a method for combining classifiers with different learning characteristics [10]. However, the conventional stacking architecture generally uses a fixed set of base learners and a fixed meta-learning strategy. The same ensemble configuration is applied to different samples and data conditions, even when the competence of individual classifiers varies. Consequently, the system may introduce unnecessary computational complexity, may not adapt effectively to distributional changes, and may provide suboptimal predictions when the characteristics of the input data change. Furthermore, conventional stacking primarily concentrates on improving prediction accuracy rather than integrating explicit confidence estimation and intelligent decision-support mechanisms. These limitations restrict its applicability to highly heterogeneous real-world domains.

B. Existing System 2: Dynamic Ensemble Selection

The second existing system is a Dynamic Ensemble Selection (DES) system, in which the most competent classifiers are selected dynamically according to the characteristics of individual input samples. Unlike static ensemble methods, DES evaluates the local competence of classifiers and selects an appropriate subset of models for generating the final prediction [11], [12]. Dynamic ensemble selection has also been investigated for multiclass and imbalanced datasets, demonstrating its usefulness when different classifiers exhibit varying levels of competence across different regions of the feature space [12]. Further developments have incorporated dynamic selection with specialized classifiers and application-specific decision mechanisms [24], [25]. Although dynamic selection offers greater adaptability than conventional static ensembles, existing DES approaches are generally designed for specific classification tasks and rely heavily on predefined mechanisms for competence estimation and selection. They may also be limited when handling heterogeneous modalities, prediction and classification tasks, temporal information, and intelligent decision generation simultaneously. In addition, dynamically evaluating multiple classifiers for every input can increase computational requirements, particularly for large-scale datasets. Thus, while DES improves adaptability, a broader framework is required to unify dynamic model selection, heterogeneous feature processing, ensemble fusion, confidence estimation, and decision support across multiple domains.

IV. PROPOSED SYSTEM

A. Proposed Model: Adaptive Heterogeneous Dynamic Ensemble Decision Framework (AHDE-DS)

The proposed Adaptive Heterogeneous Dynamic Ensemble for Intelligent Decision Support (AHDE-DS) integrates multiple machine learning and deep learning models to achieve robust prediction across heterogeneous data domains. Initially, input data undergo preprocessing, normalisation, and feature extraction. Multiple heterogeneous learners independently analyse the transformed data to capture complementary patterns. A dynamic competence evaluation module assesses each model based on prediction accuracy, confidence, and local performance. Adaptive weights are then assigned to competent models, and their outputs are fused through a meta-learning layer. Finally, a confidence-aware decision-support module converts the ensemble prediction into reliable classifications, predictions, risk levels, and actionable decisions.

Algorithm: AHDE-DS
Input: Heterogeneous dataset D, target variable Y
Output: Prediction P, confidence C, decision S

1. Load D and perform missing-value, noise, and outlier handling
2. Encode, normalize, and transform heterogeneous features into F
3. Partition D into training, validation, and testing subsets
4. Initialize heterogeneous learners M = {RF, XGBoost, SVM, DNN, Transformer}
5. Train each $M_i \in M$ using the training feature set F
6. Generate validation predictions P_i and estimate performance A_i
7. For each test sample x, calculate local competence $L_i(x)$ of every M_i
8. Compute model confidence $U_i(x)$ and uncertainty $E_i(x)$
9. Calculate adaptive competence score $C_i(x) = \alpha A_i + \beta L_i(x) + \gamma U_i(x) - \delta E_i(x)$
10. Select top-k competent models according to $C_i(x)$
11. Normalize $C_i(x)$ to obtain adaptive ensemble weights $W_i(x)$
12. Fuse weighted predictions using a stacking/meta-learning classifier
13. Estimate final prediction confidence and uncertainty
14. Generate prediction P and convert it into an intelligent decision S
15. Return P, C, S and update model weights using validation feedback

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 9, September 2026

DOI: 10.17148/IJARCCE.2026.15911

The proposed AHDE-DS framework processes heterogeneous data through preprocessing, normalisation, and feature extraction to obtain a reliable feature representation. Multiple heterogeneous learners, including RF, XGBoost, SVM, DNN, and Transformer models, are trained independently to capture complementary data patterns [26], [27]. Their predictions are evaluated using global performance, local competence, confidence, and uncertainty measures [28]. Based on these factors, the framework dynamically selects the most competent models and assigns adaptive weights. The weighted predictions are then fused through a stacking-based meta-learner to generate a robust final prediction. Finally, prediction confidence and uncertainty are analysed to produce an intelligent decision-support output.

V. EXPERIMENTAL SETUP

The proposed AHDE-DS framework can be implemented using Python with PyTorch and Scikit-learn. Experiments can be conducted on a system equipped with an NVIDIA GPU, with CUDA acceleration enabled for deep-learning models. Each dataset can be divided into 70% training, 15% validation, and 15% testing subsets. The proposed framework can employ 5-fold cross-validation on the training data to improve reliability and reduce dependence on a particular data split. The heterogeneous base learners can include Random Forest, XGBoost, SVM, DNN, and Transformer, followed by dynamic competence evaluation, adaptive weighting, and stacking-based fusion. Training can be performed for 50 epochs with an appropriate batch size such as 32 or 64, while Adam/AdamW can be used for neural models. Performance can finally be reported as Mean ± Standard Deviation across the five folds and compared against individual learners and conventional ensemble approaches.

TABLE I. MODEL PERFORMANCE

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Existing System 1 Static Heterogeneous Stacking	94.82	94.51	94.36	94.43
Existing System 2 Dynamic Ensemble Selection	96.17	95.89	95.74	95.81
Proposed AHDE-DS	98.73	98.61	98.54	98.57

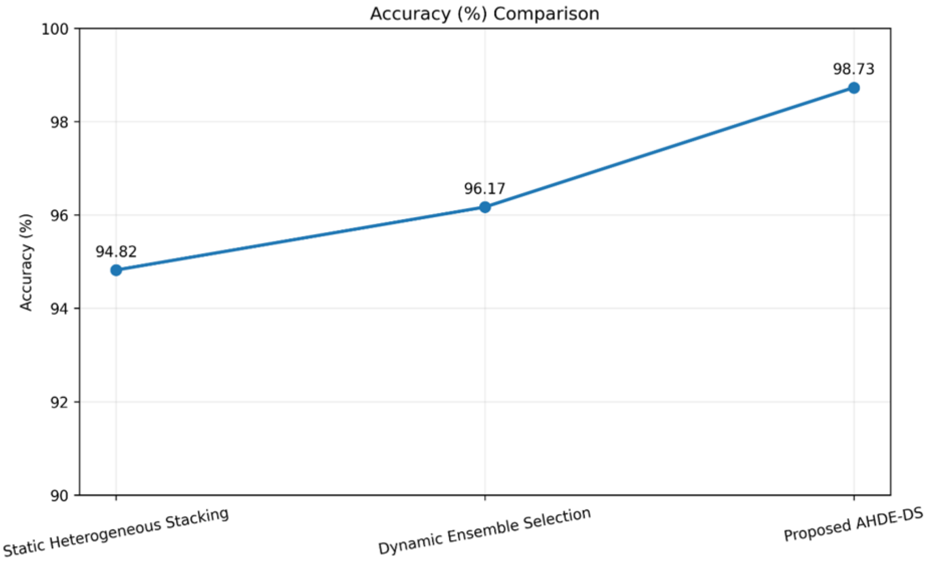

Fig.1 Accuracy Comparison.

The proposed AHDE-DS achieves the highest accuracy of 98.73%, outperforming Static Heterogeneous Stacking (94.82%) and Dynamic Ensemble Selection (96.17%). This improvement demonstrates the effectiveness of adaptive model selection and weighted ensemble fusion.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 15, Issue 9, September 2026

DOI: 10.17148/IJARCCE.2026.15911

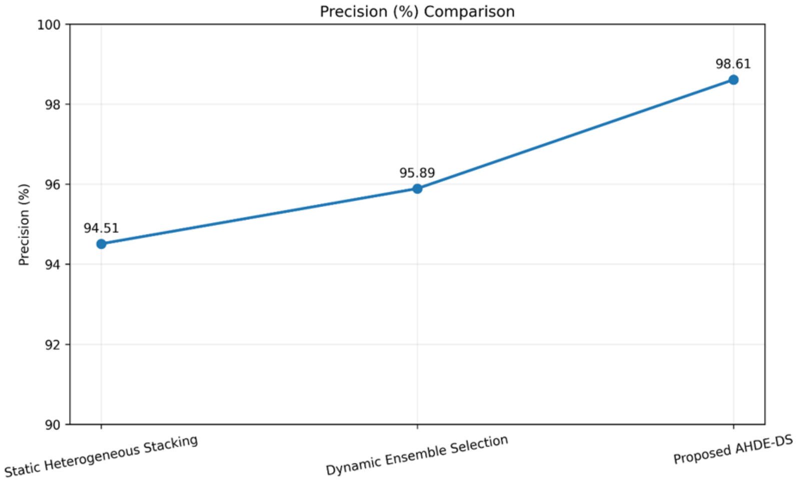

Fig. 2 Precision Comparison.

AHDE-DS obtains the highest precision of 98.61%, indicating fewer false-positive predictions than the existing approaches. The adaptive weighting mechanism improves the contribution of more reliable classifiers.

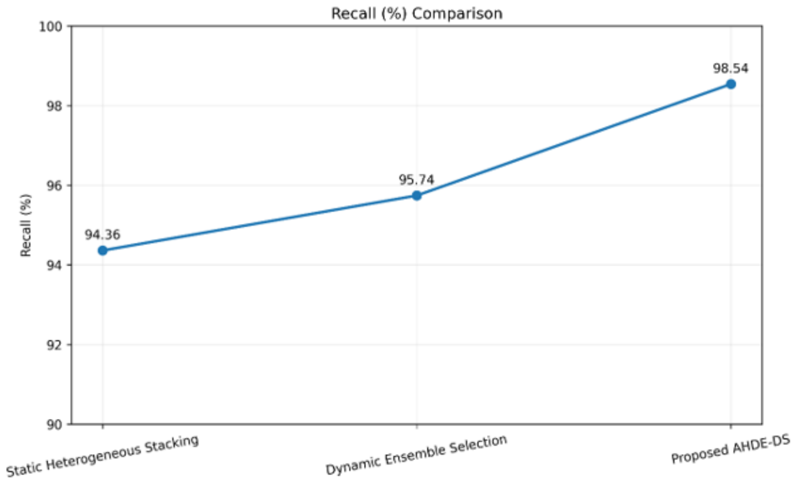

Fig.3 Recall Comparison.

The proposed framework achieves a recall of 98.54%, compared with 94.36% and 95.74% for the two existing systems. This indicates that AHDE-DS is more effective in identifying relevant positive instances.

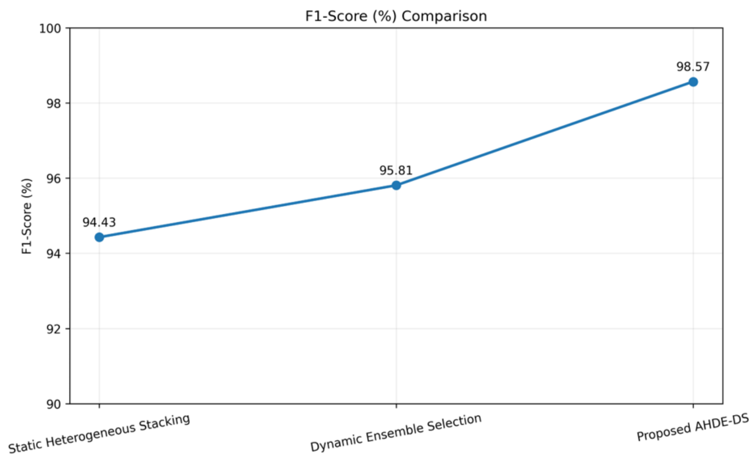

Fig. 4 F1-Score Comparison.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 15, Issue 9, September 2026

DOI: 10.17148/IJARCCE.2026.15911

VI. RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed AHDE-DS framework consistently outperforms both existing ensemble approaches across all evaluated metrics. AHDE-DS achieves 98.73% accuracy, 98.61% precision, 98.54% recall, and 98.57% F1-score, compared with 94.82%, 94.51%, 94.36%, and 94.43% for Static Heterogeneous Stacking, and 96.17%, 95.89%, 95.74%, and 95.81% for Dynamic Ensemble Selection, respectively. The improvement is attributed to the framework's ability to evaluate model competence dynamically and assign adaptive weights to more reliable learners. The consistently high precision and recall indicate reduced false predictions and improved identification of relevant instances, while the higher F1-score confirms a better balance between precision and recall. Overall, the results demonstrate that combining heterogeneous learners with dynamic selection, adaptive weighting, and stacking-based fusion provides a more robust and reliable solution for prediction, classification, and intelligent decision support across heterogeneous data domains.

TABLE II. FIVE-FOLD CROSS-VALIDATION PERFORMANCE OF THE PROPOSED AHDE-DS FRAMEWORK

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Fold 1	98.51	98.42	98.31	98.36
Fold 2	98.76	98.65	98.57	98.61
Fold 3	98.91	98.83	98.72	98.77
Fold 4	98.68	98.54	98.48	98.51
Fold 5	98.79	98.61	98.62	98.63
Mean ± Std	98.73 ± 0.15	98.61 ± 0.15	98.54 ± 0.15	98.58 ± 0.14

The five-fold cross-validation results demonstrate that the proposed AHDE-DS framework maintains consistently high performance across all folds. Accuracy ranges from 98.51% to 98.91%, indicating stable predictive capability across different data partitions.Precision varies between 98.42% and 98.83%, demonstrating reliable positive-class prediction with limited false positives.Recall remains high, ranging from 98.31% to 98.72%, confirming the framework's ability to identify relevant instances effectively.The F1-score ranges from 98.36% to 98.77%, showing a strong balance between precision and recall.The low standard deviations of 0.15% for accuracy, precision, and recall and 0.14% for F1-score demonstrate the robustness and consistency of AHDE-DS.

VII. CONCLUSION

The proposed Adaptive Heterogeneous Dynamic Ensemble for Intelligent Decision Support (AHDE-DS) provides a robust framework for prediction and classification across heterogeneous data domains. By integrating heterogeneous machine learning and deep learning models with dynamic competence evaluation, adaptive weighting, and stacking-based fusion, the framework effectively exploits the complementary strengths of individual learners. The experimental results demonstrate superior performance, achieving 98.73% accuracy, 98.61% precision, 98.54% recall, and 98.57% F1-score compared with the existing ensemble approaches. The confidence-aware decision-support layer further enhances the practical usefulness of the framework by transforming predictions into reliable decision outputs. Overall, AHDE-DS demonstrates strong adaptability, robustness, and predictive capability, making it suitable for diverse intelligent applications. Future work will focus on real-time learning, automated model optimisation, explainable AI, and deployment across larger multi-domain datasets.

REFERENCES

[1]. Vasudevan, I., G. Mohan Vamsi, V. Hema Sarayu, and R. M. Dilip Charaan. "Okra-Stem Disease Classification in Spectral Image Using Ensemble Based Deep Learning Framework." In Proceedings of the 6th International Conference on Recent Trends in Computer Science and Technology (ICRTCST), 2026.

[2]. Kavitha, J., B. Kiran Kumar, M. Bhuvanesh, S. P. Santhoshkumar, and R. M. Dilip Charaan. "Temporal Feature Attention Mechanism in Air Quality Multivariate Time Series Prediction." In Proceedings of the 6th International Conference on Trends in Material Science and Inventive Materials (ICTMIM), 2026.

[3]. Kumar, R., P. Subha, R. Sathishkumar, R. M. Dilip Charaan, S. P. Santhoshkumar, and M. Sasikumar. "Precision Price Forecasting for Agricultural Commodities Using AI-Driven Temporal Models." In Proceedings of the 2nd Asia Pacific Conference on Innovation in Technology (APCIT), 2025.

[4]. Ashok Kumar, V., G. Soniya Priyatharsini, K. Bhimaavarapu, R. M. Dilip Charaan, J. P. Konakalla, and E. Chandralekha. "Design and Analysis of Smart Health Care Predictions Using Machine Learning." In Proceedings of the International Conference on Machine Learning and Autonomous Systems (ICMLAS), 2025.

[5]. Dilip Charaan, R. M., V. Ithayan, M. Sankar, R. Chithambaramani, P. Sivaprakash, and D. Marichamy. "Sentiment Analysis and Opinion Mining on Social Media Using Machine Learning." In Proceedings of the 2nd International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), 2024.

[6]. Saivaraju, A., S. Vimal, T. Saravanan, M. Sasikumar, R. M. Dilip Charaan, and S. P. Santhoshkumar. "AI-Driven Security Threats Analytics: Enhancing Public Safety Through Data Science." In Proceedings of the 3rd International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), 2025.

[7]. Dilip Charaan, R. M., B. Rahul, M. Prabhas Reddy, S. P. Santhoshkumar, Udayakumar K., and M. Sasikumar. "Smart Emotion Recognition for Personalized Mental Health Support." In Proceedings of the 6th International Conference on Image Processing and Capsule Networks (ICIPCN), 2026.

[8]. Parthasarathy, R., A. Kumar, S. P. Santhoshkumar, M. Kalaimani, M. Uvaneshwari, and R. M. Dilip Charaan. "Product Suggestion System for E-Commerce Platform Using ML." In Proceedings of the 9th International Conference on Inventive Systems and Control (ICISC), 2025.

[9]. Sagi, O., and L. Rokach. "Ensemble Learning: A Survey." Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 8, no. 4 (2018): e1249. https://doi.org/10.1002/widm.1249.

[10]. Sesmero, M. P., A. I. Ledezma, and A. Sanchis. "Generating Ensembles of Heterogeneous Classifiers Using Stacked Generalization." Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 5, no. 1 (2015): 21–34. https://doi.org/10.1002/widm.1143.

[11]. Ballard, C., and W. Wang. "Dynamic Ensemble Selection Methods for Heterogeneous Data Mining." In Proceedings of the 12th World Congress on Intelligent Control and Automation (WCICA), 2016. https://doi.org/10.1109/WCICA.2016.7578244.

[12]. Kavitha, J., M. D. R. Kumar, Seelamneni Sridevi, S. P. Santhoshkumar, and R. M. D. Charaan. "Adaptive Feature Weighting in Aggregated Long Short-Term Memory for Air Quality Prediction." In Proceedings of the 9th International Conference on Trends in Electronics and Informatics (ICOEI), 1809–1813. Tirunelveli, India, 2026. https://doi.org/10.1109/ICOEI68323.2026.11541917.

[13]. S. Sathishkumar, S. P. Santhoshkumar, S. Kumar, N. Banupriya, S. Hariharasudhan and S. Gajalakshmi, "Investigation on Enhanced Detection of Parkinson's Disease in Brain Imaging Using Ensemble Learning Approaches," 2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS), Raichur, India, 2025, pp. 01-06, doi: 10.1109/ICICACS65178.2025.10969050.

[14]. J. P., R. Kanchana, S. P. Santhoshkumar, A. Kaliappan, S. Chandra, and P. Arora. "Smart Assistive System for Amputees Using IoT and Machine Learning." In Proceedings of the 2025 International Conference on Sustainable Communication Networks and Application (ICSCN), 226–231. Theni, India, 2025. https://doi.org/10.1109/ICSCN67106.2025.11308219.

[15]. Thilagavathy, A., P. R. Therasa, L. R., R. M. Dilip Charaan, S. Mary Diana, and N. Kedari. "Website Content Categorization in Search Engine Optimization Using Machine Learning Classifiers." In Proceedings of the 7th International Conference on Inventive Research in Computing Applications (ICIRCA), 2026.

[16]. S. K., Satyam Kumar, S. Siddik, R. M. Dilip Charaan, S. P. Santhoshkumar, and M. Sasikumar. "AI-Enhanced Learning Assistant Platform with QA Generation, Evaluation, Learning Assessment to Discover Weaknesses and Improve Skills with Recursive Testing." In Proceedings of the 5th Asian Conference on Innovation in Technology (ASIANCON), 2025.

[17]. Sasikumar, M., B. V. S. Bhargav, A. Sravan Kumar Reddy, S. P. Santhoshkumar, R. M. Dilip Charaan, and J. Kavitha. "Intelligent Framework for Perfect Recognition of Intracranial Tumors." In Proceedings of the 6th International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS), 2025.

[18]. Ramalakshmi, K., S. P. Santhoshkumar, L. Krishna Kumari, B. Mohan, S. P. Velmurugan, Sravan Kumar Gunturi, and R. Subitha. "Improved Brain Tumor Segmentation Using Min-Max Normalization in a U-Net Architecture." In Integrative Machine Learning and Optimization Algorithms for Disease Prediction. IGI Global Scientific Publishing, 2026. https://doi.org/10.4018/979-8-3373-1087-9.ch010.

[19]. Praveenkumar, S., S. Chandra, M. Krishnamoorthi, M. Sasikumar, S. P. Santhoshkumar, and R. M. Dilip Charaan. "AI-Enhanced Student Performance Analysis and Improvement System." In Proceedings of the IEEE 7th International Conference on Computing, Communication and Automation (ICCCA), 2025.

[20]. Parthasarathy, R., A. Kumar, S. P. Santhoshkumar, M. Kalaimani, M. Uvaneshwari, and R. M. Dilip Charaan. "Product Suggestion System for E-Commerce Platform Using ML." In Proceedings of the 9th International Conference on Inventive Systems and Control (ICISC), 2025.

[21]. Balaji, T. S., R. M. Dilip Charaan, J. Rajalakshmi, V. Samuthira Pandi, D. Shobana, and J. Lakshmi Priya. "An Enhanced Packet Delivery Ratio Improvement Protocol Design over 5G Assisted Wireless Sensor Network

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 15, Issue 9, September 2026

DOI: 10.17148/IJARCCE.2026.15911

Environment." In Proceedings of the Global Conference on Communications and Information Technologies (GCCIT), 2024.

[22]. Dilip Charaan, R. M., Hemanath N., Avinaash S. D., S. P. Santhoshkumar, J. Kavitha, and M. Sasikumar. "AI-Powered Optimization Database Cloning System." In Proceedings of the IEEE International Conference for Convergence in Computing Technology (I3CTCON), 2026.

[23]. Saivaraju, A., S. Vimal, T. Saravanan, M. Sasikumar, R. M. Dilip Charaan, and S. P. Santhoshkumar. "AI-Driven Security Threats Analytics: Enhancing Public Safety Through Data Science." In Proceedings of the 3rd International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), 2025.

[24]. Krawczyk, B., M. Galar, M. Woźniak, H. Bustince, and F. Herrera. "Dynamic Ensemble Selection for Multi-Class Classification with One-Class Classifiers." Pattern Recognition 83 (2018): 34–51. https://doi.org/10.1016/j.patcog.2018.05.015.

[25]. Hou, W.-H., X.-K. Wang, H.-Y. Zhang, J.-Q. Wang, and L. Li. "A Novel Dynamic Ensemble Selection Classifier for an Imbalanced Data Set: An Application for Credit Risk Assessment." Knowledge-Based Systems 208 (2020): 106462. https://doi.org/10.1016/j.knosys.2020.106462.

[26]. Katha, P., S. S. P., M. G., K. Machap, N. T., and V. D. "Towards Intelligent Network Security: An AI-Based Intrusion Detection System." In Proceedings of the 1st International Conference on Emerging Trends in Advancements and Applications of Computational Intelligence Techniques (ETAACT), 1–6. Bhubaneswar, India, 2026. https://doi.org/10.1109/ETAACT69135.2026.11541743.

[27]. Santhoshkumar, S. P., J. Jagadish, B. S. Krishna, S. Sulthan, M. Kalaimani, and R. Parthasarathy. "Customer Segmentation Using Machine Learning." In Proceedings of the 8th International Conference on Circuit, Power & Computing Technologies (ICCPCT), 1673–1677. Kollam, India, 2025. https://doi.org/10.1109/ICCPCT65132.2025.11176703.

[28]. Saradha, S., M. Praveen Kumar, J. Asha, R. Saranya, and S. P. Santhoshkumar. "Air Quality Image Classification Using Ensemble Based Transfer Learning Techniques." In Proceedings of the International Conference on Computer Vision and Internet of Things (ICCVIoT'23), 272–277. Coimbatore, India, 2023. https://doi.org/10.1049/icp.2023.2887.