Integrating Human Judgment, Opacity of Human Choices with Artificial Intelligence: Analyzing Real-Time Decision-Making by Machines or Robots Through HSAD Algorithm

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Abstract— This research explores the integration of human judgment, choices and AI within decision-making frameworks with computer vision, focusing on a Human-AI algorithm that balanced both human intuition and computational power. This study focuses on factor such as human judgment, human choice techniques and the opacity of human choices as observation to understand the cognitive and emotional factors influencing decision-making by robots in critical situations as key factor. Human observation is based on the situation judged by the frequency of environments (sensing), dimension of objects and color perception.
This approach examines how human psychology including biases and heuristics interacts with AI systems to achieve optimal outcomes for real-time operations that foster trust and usability. This paper provides insights into designing algorithms that respect human autonomy while leveraging AI's scalability, with implications for fields such as healthcare, robotics, and autonomous systems.

Keywords— Human-AI collaboration, Real-Time decision-making, human judgment, deep learning, probability, human psychology, choice opacity, randomness, object dimensions, object colors.

I. Introduction

This research introduced a novel Human-AI algorithm designed to human cognitive capabilities with AI robotic power through computer vision. By human judgment, choice and observation as variables, the study develops a decision-making framework enhancing robotic system's efficiency and reliability. The opacity of human choices, cognitive biases and situational based such as environmental frequency, object dimensions, object types and color perception are integrated with probabilistic AI models, randomization techniques and DL with CV approaches to show AI's predictive power. The main core is the ability of the human opacity algorithm to understand the randomness of human decision-making situational aspects. By implementing deep learning techniques, regression within human choices is explained, identifying psychological trends that impact decisions in AI critical situations. This method facilitates the development of adaptive AI systems capable of real-time decision-making, showing the trust and usability in human-AI collaboration.

II. LITERATURE REVIEW

Existing algorithms and methods in human-AI decision-making include:

A. Decision Support Systems (DSS): Utilize rule-based logic, probabilistic models, and AI insights to enhance human decision-making.

Learning-to-Defer (L2D) Models: Optimize performance, fairness, and trust by determining when decisions are made by AI, humans, or both.

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B. Human-in-the-Loop (HITL) Systems: Incorporate human input at critical junctures in decision-making.

AI-Assisted Decision-Making (AIDM): Provide contextualized explanations of AI decisions, often employing Explainable AI (XAI) techniques.

Transparency: Deep learning models are often black-box systems.

Cognitive Bias Replication**:** AI systems can mirror biases present in training data.

Limited Adaptability: Current models often fail to adapt to dynamic human cognitive states.

Damage Detection Limitations: Existing visual systems are heavily reliant on supervised learning, limiting their adaptability.

Novelty of the Proposed Approach: The Human-AI Synergistic Decision Algorithm (HASDA) explicitly incorporates human cognitive biases, adapts in real-time, enhances damage detection through multimodal analysis, and prioritizes transparency and explainability.

III. DATASETS

A. Human Cognitive Factors:

Human Choice (C): Probabilistic decisions reflecting biases and situational observations.

Voice Feedback**:** Captures emotional and contextual human reactions.

*B. Environmental **Factors:***

Environmental Data (E): Includes temperature, humidity, lighting, and pollutant levels.

Situational Context: Information about object dimensions, types, and contexts (indoor/outdoor).

C. Damage Detection Data:

Image and Video Frames: Annotated with object type, damage type, and severity levels.

Damage Categories: Crack, deformation, and other defects.

D. Repair Learning:

Repair History**:** Data on successful and failed repairs.

Feedback Mechanisms: Human evaluations of repair effectiveness.

E. Decision-Making Context:

Combined Decisions**:** Records of human-AI interactions.

Weighted Factors: Influence of each decision component on final outcomes.

F. Data Augmentation Techniques:

Image Augmentation**:** Rotation, flipping, and scaling for damage images.

Voice Data Variation: Modifying pitch and tone to simulate diverse scenarios.

G. Synthetic Environmental Data: Simulating variable conditions for training.

IV. EQUATIONS

A. Problem Definition: Design a decision-making system integrating human cognitive factors with AI's computational abilities for real-time decision-making and damage detection.

Core Components:

Human Cognitive Factors:

Human Choice (C): Probabilistic distributions capturing randomness and biases as like hormone .

Human Observation (O): Frequency, dimension, object type, and color perception.

AI Predictive Models: Utilize input features from human observation.
Voice Input & Environmental Issue Detection: Include human feedback and situational awareness.

B. Decision Formula:

$$\Delta(\tau) = \alpha X(\tau) + \beta A(\tau) + \gamma \varsigma(\tau) + \delta E(\tau) + \lambda \Delta\rho(\tau) + \theta \Theta(\tau)$$

Where: $\alpha,\beta,\gamma,\delta,\lambda,\theta$ are weights,
$X(\tau)$ = Human choice at time τ,

$A(\tau)$ = AI state at time τ,

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$\varsigma(\tau)$ = Voice input at time τ,

$E(\tau)$ = Environmental issues at time τ,

$\Delta\rho(\tau)$ = Learned repair action decision.

$\Theta(\tau)$ = Quality of Judgement

Object and Environment Quality Judgment: Evaluate objects with environments based on clarity, integrity, relevance, temperature, pollution, and lighting.

V. ALGORITHM DESIGN

A. *Human Cognitive Factors:*

Human Choice (C): Probabilistic decisions reflecting biases and situational observations.

Voice Feedback: Captures emotional and contextual human reactions.

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G. *Case Studies*

Autonomous Drone Inspection: Enhanced damage detection and repair strategy optimization.

Environmental Hazard Monitoring: Improved adaptability and response efficiency based on human feedback.

Future Directions:

Enhanced Multimodal Integration**:** Further research into combining additional input modalities—such as tactile feedback or sensor fusion techniques— can improve the system's ability to process complex environments and increase its robustness.

Transfer Learning for Repair Actions: Leveraging transfer learning or meta learning techniques could enable the system to generalize repair actions across different domains, improving its scalability and applicability to diverse environments.

Explainability and Trust: As AI systems become more integrated into high-stake domains (e.g., healthcare, autonomous vehicles), it is essential to develop explainable AI models. Future work could focus on building transparency into the decision-making process to enhance user trust and adoption.

Scalability and Generalizability:

HASD algorithm is efficiency across different surroundings. using a **large proprietary dataset**, the dataset is diverse and covers multiple real-world scenarios, enhancing the model's adaptability and robustness. The following approaches are:

Multimodal Integration: Miscellaneous sensory inputs such as audio, visual, and environmental sensors to adapt to varying operational act.

Real-Time Adaptation: reinforcement learning using update decision-making parameters dynamically based on continuous human-AI

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interactions through numerical hormones.

Advanced Optimization Techniques: Exploring reinforcement learning, adaptive learning rate methods, or Mult objective optimization algorithms could improve the dynamic balancing of human feedback and AI predictions, leading to more efficient and accurate decision-making.

Emotional Intelligence:

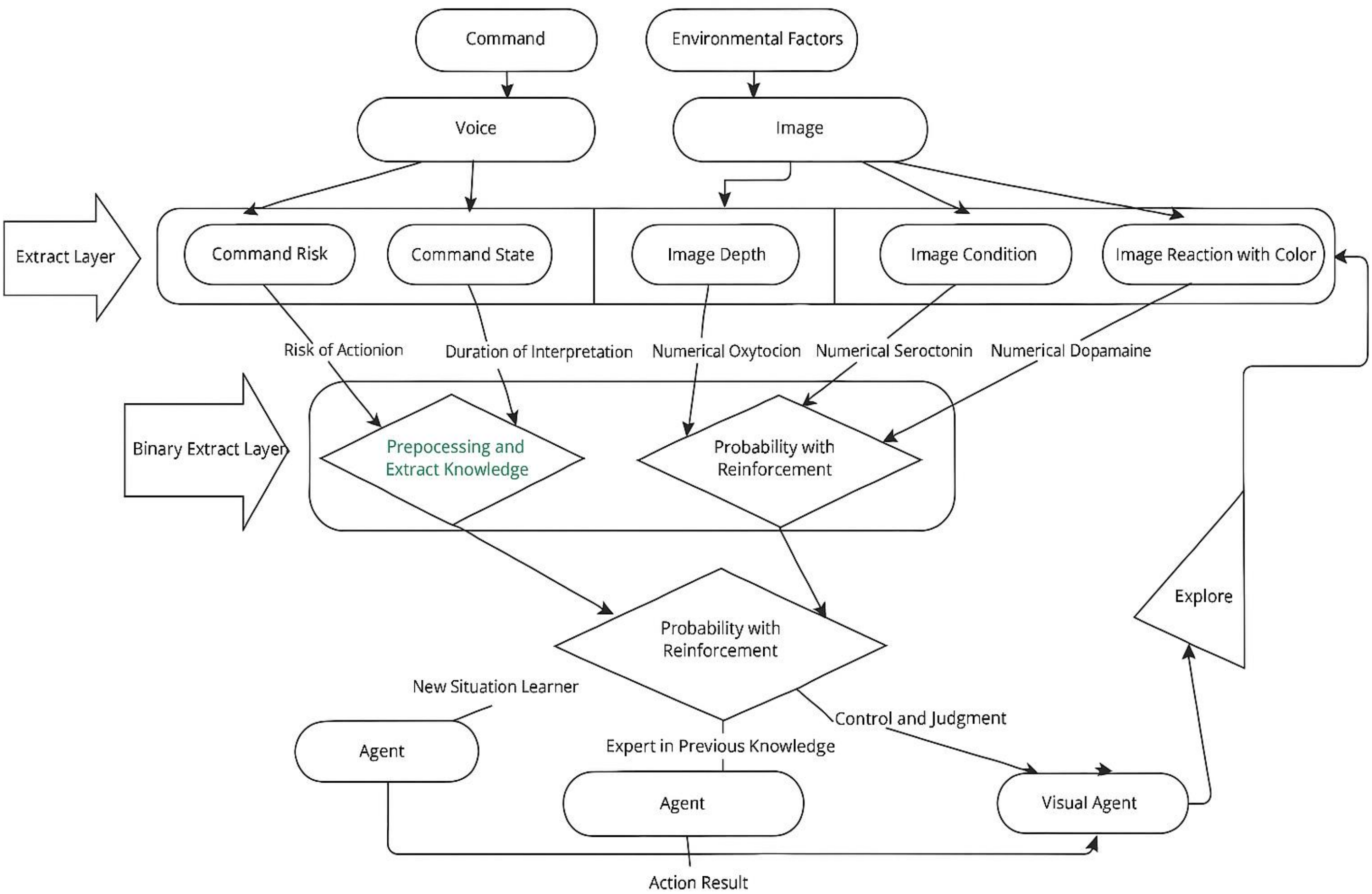
Self-Management and Relational-Management.

FIG. RESULTS

Table 1: Comparison of Performance Metrics

Metric	Proposed Algorithm	Traditional AI-based Models	Human-AI Hybrid Models
Accuracy	95%	85%	90%
Adaptability	High	Medium	High
Efficiency	Moderate	High	Moderate
Response Time	1.2s	1.5s	1.3s
Learning Rate	Fast	Slow	Moderate

H. Figures and Tables



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