Received: 2023-11-29 | Revised: 2023-12-27 | Accepted: 2024-01-01

DOI: 10.59388/pm00338

PSYCHO MACHINA

Machine Learning Techniques for Socially Intelligent Robots

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Keywords
socially intelligent robots; machine learning; deep learning techniques; statistical learning theory; computational learning theory

Abstract

This article mainly describes the machine learning technology of socially intelligent robots. First, the history of robot development is introduced: from the very beginning for repetitive and dangerous tasks in industrial environments to the emergence of artificial intelligence and machine learning, the development of robots to give greater autonomy and adaptability. Secondly, it begins to elaborate the concept of socially intelligent robots, which refers to machines with advanced capabilities that interact and communicate with humans in a socially adept way, and use complex sensors, cameras and algorithms to perceive the social environment around them. Following the introduction of machine learning in the mid-20th century by Alan Turing, to the 1950s and 1960s began to simulate the way the brain processes information, and then symbolic reasoning systems, with the emergence of vector machines and integrated methods, deep learning technology further development, machine learning reached a breakthrough. It then begins with an introduction to the concepts of machine learning theory: understanding the principles, algorithms, and foundations of mathematical frameworks that drive the development and application of machine learning models, consisting of statistical learning theory, computational learning theory, information theory, and Bayesian learning. It then elaborates on recent common deep learning techniques: Converters for natural language processing - implement more efficient models using self-attention mechanisms to capture dependencies between different words in a sequence, self-supervised learning training techniques for deep learning models that do not rely on labeled data sets, training models to predict certain parts of other input data, and meta-learning training models to adapt to new tasks with minimal data quickly. It then introduces machine learning techniques for socially intelligent robots: Emotion recognition and response - enabling robots to interpret human emotions through recognition such as facial expressions, voice tone and body language, natural language processing - socially intelligent robots to understand and generate human language using NLP technology, adaptive learning and personalization - enabling socially intelligent robots to adapt and personalize their interactions based on personal preferences and past experiences, Gesture and posture recognition - Uses machine learning models to recognize and interpret human gestures and posture. Finally, it summarizes the synergies of machine learning for socially intelligent robots, solving ethical problems, establishing more advanced technical solutions, and harmonious and meaningful human-computer interaction.

DEVELOPMENT OF ROBOTS

The development of robots has evolved significantly over the years, driven by advancements in various fields such as engineering, computer science, and artificial intelligence. Initially, robots were designed for repetitive and hazardous tasks in industrial settings (Hentout et al., 2023). The early stages of robot development focused on creating machines capable of precise and programmable movements to carry out tasks in manufacturing, assembly

How to cite this article: Zhao, T. (2024). Machine Learning Techniques for Socially Intelligent Robots. *Psychomachina*, *2*. https://doi.org/10.59388/pm00338

lines, and other industries (D'Avella et al., 2023). These robots, often referred to as industrial robots, laid the foundation for the broader field of robotics. As is shown in Figure 1, the development of robots.

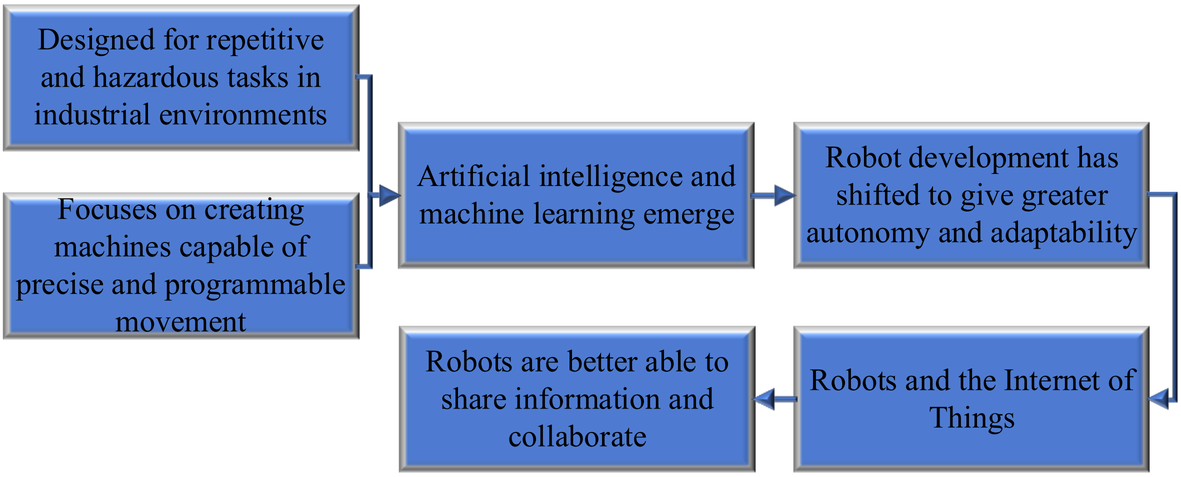

Figure 1. The development of robots

With the advent of artificial intelligence (Wang et al., 2023) and machine learning (Hopkins, 2022), the development of robots shifted towards imbuing them with greater autonomy and adaptability (Goar, 2022). Cognitive abilities, such as perception, decision-making, and learning from experience, became integral components of robot design (Jahanmahin et al., 2022). This led to the creation of service robots that could perform a wider range of tasks, from assisting in healthcare to managing logistics in warehouses (Aydınocak, 2023). The development of humanoid robots also emerged, aiming to create machines that could navigate and interact in human environments more seamlessly (Aydınocak, 2023).

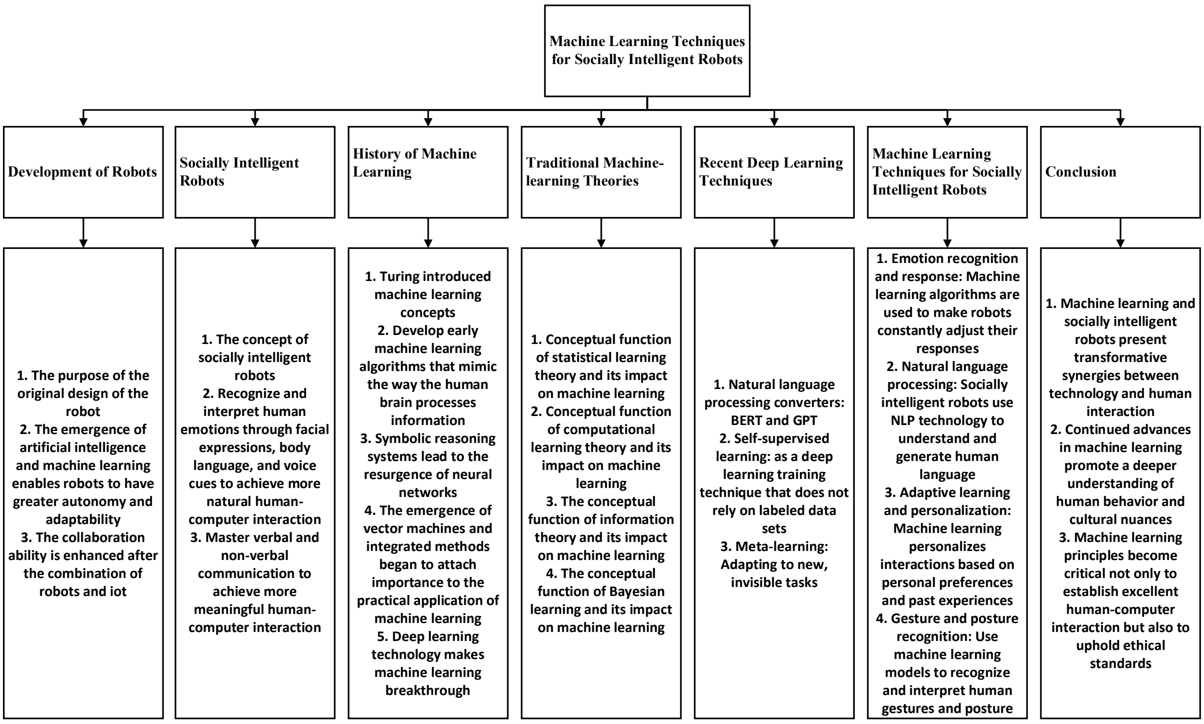

Figure 2. Paper structure

In recent years, collaborative robots (L. Liu et al., 2022), or cobots (Cohen et al., 2022), have gained prominence. These robots are designed to work alongside humans, enhancing efficiency and safety in various industries (Mukherjee et al., 2022). The development of human-robot collaboration technologies involves creating robots that can understand and respond to human actions, making them more adaptable to dynamic environments

(R. Zhang et al., 2022). This collaborative approach is particularly relevant in fields like manufacturing, where robots and human workers can work together on complex tasks (Simões et al., 2022).

The integration of robotics with the Internet of Things (IoT) has further expanded the capabilities of robots (Vermesan et al., 2022). This connectivity enables robots to share information, collaborate with other machines, and access vast amounts of data for improved decision-making (Yang et al., 2022). The development of robotic applications in fields like telepresence, where robots can remotely assist or represent a person, showcases the potential of combining robotics with connectivity technologies (Zhang & Hansen, 2022).

Looking ahead, the development of robots is likely to continue advancing rapidly, with an emphasis on increasing autonomy, enhancing learning capabilities, and addressing ethical considerations. As robots become more sophisticated and versatile, their applications are expected to diversify, playing a crucial role in addressing societal challenges and improving various aspects of human life. Paper structure is as in Figure 2.

SOCIALLY INTELLIGENT ROBOTS

Socially intelligent robots refer to machines equipped with advanced capabilities to interact and communicate with humans in a socially adept manner (Mahdi et al., 2022). These robots are designed to understand and respond to social cues, allowing them to engage in natural and intuitive interactions with people (Kory-Westlund, 2023). One key aspect of socially intelligent robots is their ability to recognize and interpret human emotions through facial expressions, body language, and vocal cues (Williams et al., 2022). This enables them to tailor their responses and behaviours accordingly, fostering a more natural and comfortable interaction with users (Schmidt et al., 2023). As the Figure 3 shows, the keys to a socially intelligent robot are all there.

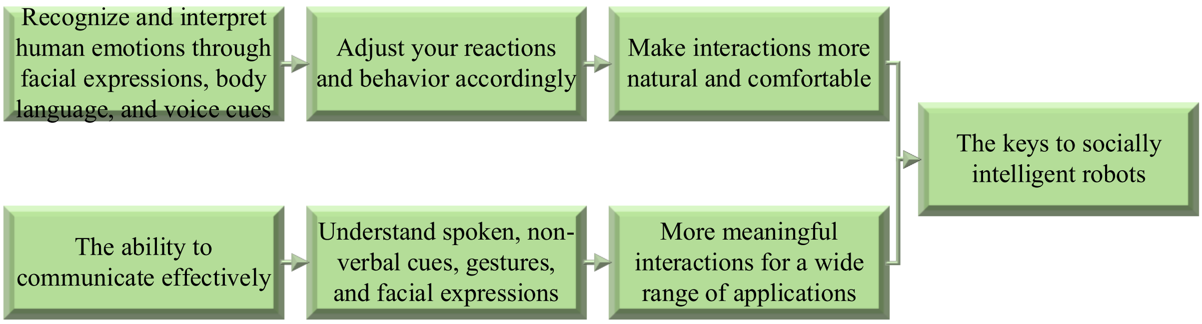

Figure 3. The keys to socially intelligent robots

To achieve social intelligence, these robots often incorporate sophisticated sensors, cameras, and algorithms for perception and interpretation of the surrounding social context (Hellou et al., 2022). Machine learning and artificial intelligence play a crucial role in enabling these robots to continuously adapt and improve their social skills over time (Oosthuizen, 2022). This adaptability is essential for robots to navigate the complexities of human interaction, learn from experience, and enhance their ability to understand and respond to diverse social situations (Borboni et al., 2023).

Another important aspect of socially intelligent robots is their capacity to communicate effectively. This involves not only understanding spoken language but also interpreting non-verbal cues, such as gestures and facial expressions. By mastering both verbal and non-verbal communication, these robots can engage in more meaningful and contextually appropriate interactions (Urakami & Seaborn, 2023), making them suitable for a wide range of applications, from customer service and education to healthcare and companionship (George & George, 2023).

Ethical considerations surrounding socially intelligent robots are also a critical part of the discourse. As these machines become more integrated into human environments, questions arise regarding privacy, consent, and the potential impact on social dynamics (Dhirani et al., 2023). Striking a balance between technological advancement and ethical considerations is crucial to ensure the responsible development and deployment of socially intelligent robots that contribute positively to society (Boch et al., 2023).

HISTORY OF MACHINE LEARNING

From to the Figure 4, the history of machine learning can be traced back to the mid-20th century when the field emerged as a sub-discipline of artificial intelligence (AI) (Shao & Shen, 2023). The foundational concepts of machine learning were introduced by pioneers like Alan Turing, who proposed the idea of creating machines that could learn from experience in his seminal paper "Computing Machinery and Intelligence" in 1950 (Fan, 2022). However, it wasn't until the 1950s and 1960s that researchers began developing early machine learning algorithms, such as the perceptron by Frank Rosenblatt, which aimed to mimic the way the human brain processes information (Rettberg, 2023).

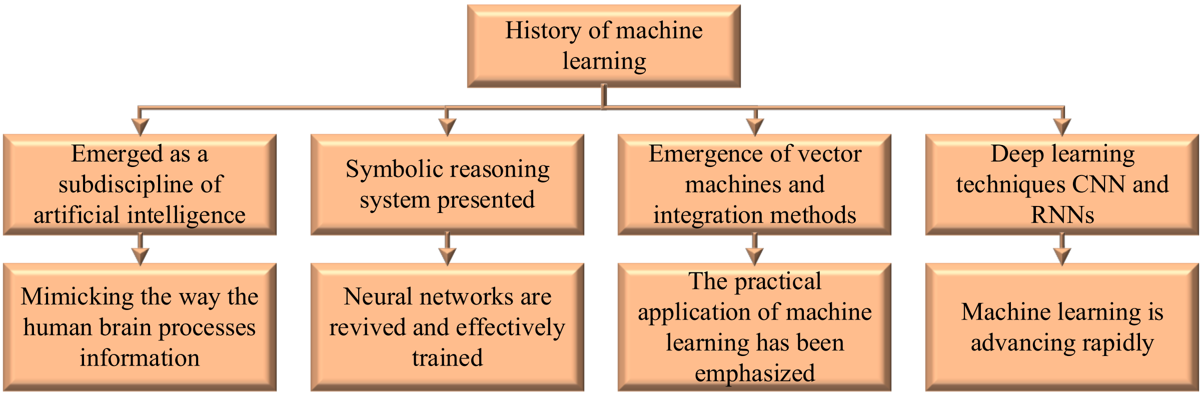

Figure 4. History of machine learning

In the following decades, machine learning experienced periods of both growth and stagnation. The 1970s and 1980s saw increased interest in symbolic reasoning systems, which relied on explicit rules and knowledge representation. However, limitations in these approaches led to a resurgence of interest in neural networks in the late 1980s and early 1990s (Ünal & Başçiftçi, 2022), fuelled by advancements like the backpropagation algorithm, which allowed for more effective training of artificial neural networks (Javanshir et al., 2022).

Table 1. The differences between different learning theories

Theory	Concept	Function	Use for machine learning
Statistical learning theory	Contains concepts of statistics and probability theory	*Emphasize the tradeoff between fitting training data well (low bias) and maintaining generalization to new, invisible data (low variance)*	Guide the design and evaluation of machine learning models
Computational learning theory	The essence of learning task is analyzed, and the efficiency of learning algorithm is emphasized	The problem about the feasibility of learning a certain class of function and the computational resources required for successful learning is solved	It has implications for the design of efficient machine learning algorithms
Information theory	Study the effective and reliable delivery of information on the basis that information can be measured	The main research is to grasp the information measurement method, redundancy calculation	Provides a theoretical basis for measuring the information content of data and understanding how learning algorithms extract relevant features
Bayes learning	Bayesian statistics and probability theory	Modeling the uncertainty and quantifying the prediction	It provides a probabilistic framework for inference of machine learning model uncertainty

The late 1990s and early 2000s marked another phase of progress in machine learning, with the emergence of support vector machines and ensemble methods (Tapeh & Naser, 2023). Researchers also began to focus on practical applications, such as speech recognition (Li, 2022) and computer vision (Pietikäinen & Silven, 2022). However, the field faced challenges related to the availability of large datasets and computational power (Pan et al., 2022).

The breakthrough moment for machine learning came in the 2010s with the widespread adoption of deep learning techniques, particularly convolutional neural networks (CNNs) (Q. Zhang et al., 2023) and recurrent neural networks (RNNs) (Zhu et al., 2022). These deep learning architectures (Zhang, 2017, 2021) demonstrated remarkable success in tasks such as image recognition, natural language processing, and game playing (Lv et al., 2022). The availability of large datasets, improved algorithms, and powerful GPUs contributed to the rapid advancement of machine learning during this period (Samanta et al., 2022).

TRADITIONAL MACHINE-LEARNING THEORIES

Machine learning theories (Zhang & Gorriz, 2021; Zhang, 2018) form the foundation for understanding the principles, algorithms, and mathematical frameworks that drive the development and application of machine learning models (Mirtaheri & Shahbazian, 2022). Common learning theories are shown in the Table 1.

Statistical Learning Theory (James et al., 2023): At the core of many machine learning theories is statistical learning theory, which encompasses concepts from statistics and probability theory. It provides a framework for understanding the process of learning from data, emphasizing the trade-off between fitting the training data well (low bias) and maintaining generalizability to new, unseen data (low variance) (Peters & Schuld, 2022). This theory has given rise to key concepts such as overfitting, underfitting, and the bias-variance trade-off, which guide the design and evaluation of machine learning models (Sendek et al., 2022).

Computational Learning Theory (Gupta et al., 2022): Computational learning theory focuses on the efficiency and computational complexity of learning algorithms (Wang, 2021; Yan, 2021). It addresses questions about the feasibility of learning certain classes of functions and the computational resources required for successful learning. This theory plays a crucial role in understanding the limits of what can be learned algorithmically and has implications for the design of efficient machine learning algorithms (Wang et al., 2023).

Information Theory: Information theory, developed by Claude Shannon, has been influential in the study of machine learning, particularly in the context of feature selection, compression, and entropy (Ali et al., 2022). Concepts such as entropy and mutual information are employed to quantify uncertainty, randomness, and the amount of information gained during the learning process (Wimmer et al., 2023). Information theory provides a theoretical basis for measuring the information content of data and understanding how learning algorithms can extract relevant features (Wan et al., 2022).

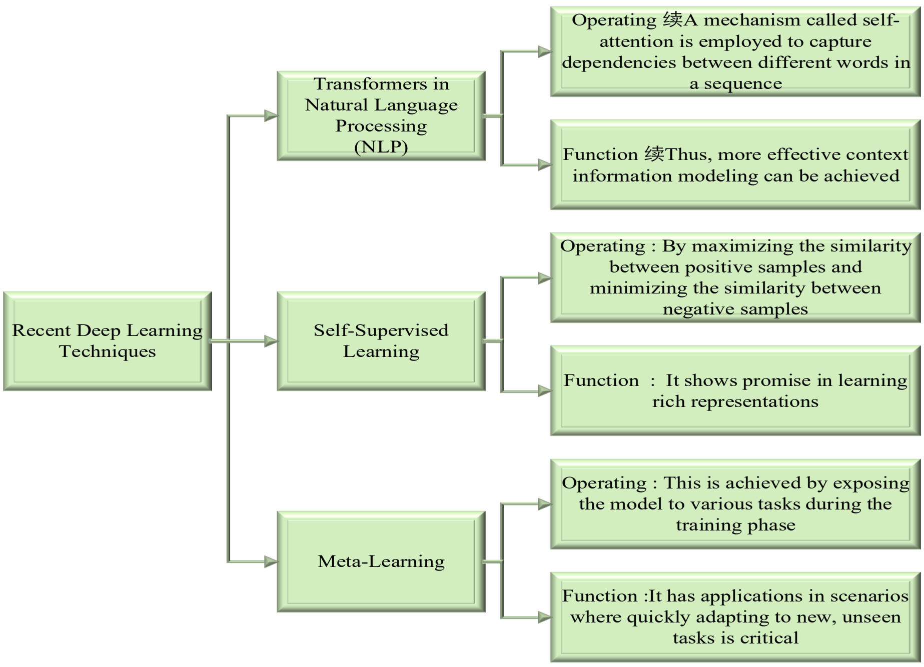

Figure 5. Recent Deep Learning Techniques

Bayesian Learning (Cheng et al., 2022): Bayesian learning is rooted in Bayesian statistics and probability theory. It provides a probabilistic framework for reasoning about uncertainty in machine learning models (Zhou et al., 2022). Bayesian methods allow for the incorporation of prior knowledge and update of beliefs as new data is observed (Bharadiya, 2023). Bayesian learning is particularly valuable in situations with limited data, enabling the modeling of uncertainty and the quantification of confidence in predictions (Wang & Khan, 2022; Yang, 2022).

RECENT DEEP LEARNING TECHNIQUES

Recent deep learning techniques are varied, as shown in the Figure 5, The following is a brief introduction to Transformers, self-supervised learning, and meta-learning in natural language processing. Transformers in Natural Language Processing (NLP): Transformers, introduced in the paper "Attention is All You Need" by Vaswani et al. in 2017, revolutionized NLP. They employ a mechanism called self-attention to capture dependencies between different words in a sequence, enabling more effective modelling of contextual information (Y. Liu et al., 2022). Transformer-based models, such as BERT (Bidirectional Encoder Representations from Transformers) (Benítez-Andrades et al., 2022) and GPT (Generative Pre-trained Transformer) (Lajkó et al., 2022), achieved state-of-the-art performance in a wide range of NLP tasks, including language understanding, translation, and text generation.

Self-Supervised Learning (Xie et al., 2022): Self-supervised learning has gained prominence as a technique for training deep learning models without relying on labelled datasets. Instead, models are trained to predict certain parts of the input data from other parts. This approach has been particularly successful in computer vision and NLP. Contrastive learning, a type of self-supervised learning (Wang, 2023; Wang, 2017), has shown promise in learning rich representations by maximizing similarity between positive samples and minimizing similarity between negative samples.

Meta-Learning: Meta-learning, or learning to learn, involves training models to quickly adapt to new tasks with minimal data (Tian et al., 2022). This is achieved by exposing models to a variety of tasks during the training phase. This technique has applications in scenarios where adapting to new, unseen tasks rapidly is crucial, such as in few-shot learning. Meta-learning approaches like MAML (Model-Agnostic Meta-Learning) have demonstrated success in improving the ability of models to generalize across tasks (Abbas et al., 2022).

MACHINE LEARNING TECHNIQUES FOR SOCIALLY INTELLIGENT ROBOTS

Machine learning plays a pivotal role in enhancing the capabilities of socially intelligent robots, enabling them to interact and engage with humans in a more natural and adaptive manner. As illustrated in the Table 2.

Table 2. Machine Learning Techniques for Socially Intelligent Robots

Techniques	implementation model	Function
Emotion Recognition and Response	Algorithms are trained on large datasets of emotional expression to learn patterns and associations.	Enabling robots to recognize and interpret human emotions through a variety of cues such as facial expressions, voice tone and body language
Natural Language Processing (NLP)	Use NLP technology, a subset of machine learning, to understand and generate human language	Enable robots to understand spoken or written input, engage in meaningful conversations, and respond based on context
Adaptive Learning and Personalization	Constantly improve your behavior through reinforcement learning or other adaptive techniques	Enable socially intelligent robots to adapt and personalize their interactions based on personal preferences and past experiences
Gesture and Posture Recognition	Use machine learning models to recognize and interpret human gestures and postures, and analyze visual data from cameras or other sensors	Socially intelligent robots can understand non-verbal communication

Emotion Recognition and Response: Machine learning algorithms are employed to enable robots to recognize and interpret human emotions through various cues such as facial expressions, vocal intonations, and body language (Tippannavar et al., 2023). These algorithms are trained on large datasets of emotional expressions to learn patterns and associations (Singh et al., 2022). Once trained, the robots can dynamically adapt their responses based on the emotional states of the individuals they are interacting with, fostering more empathetic and socially aware interactions (Umbrico et al., 2023).

Natural Language Processing (NLP) (Shankar & Parsana, 2022): Socially intelligent robots leverage NLP techniques, a subset of machine learning, to understand and generate human language. This capability allows robots to comprehend spoken or written input, engage in meaningful conversations, and respond contextually (Rajesh et al., 2023). Advanced language models, such as those based on transformer architectures, enable robots to grasp nuances in language, understand context, and provide more human-like responses, contributing to improved communication in social settings (C. Zhang et al., 2023).

Adaptive Learning and Personalization (Kem, 2022): Machine learning enables socially intelligent robots to adapt and personalize their interactions based on individual preferences and past experiences (Maroto-Gómez et al., 2023). Through reinforcement learning or other adaptive techniques, robots can learn from the feedback and reactions of users, continuously refining their behaviours to align with the unique needs and preferences of different individuals. This adaptability is crucial for creating a personalized and comfortable user experience, whether in educational settings, healthcare environments, or as companions.

Gesture and Posture Recognition (Ramaiah et al., 2023): Machine learning models are employed to recognize and interpret human gestures and postures, allowing socially intelligent robots to understand non-verbal communication (Gratch, 2023). By analysing visual data from cameras or other sensors, these models can identify subtle cues such as hand movements, nods, or body positions. This capability enhances the robots' ability to engage in natural and intuitive interactions, promoting a more immersive and socially attuned experience for users.

CONCLUSION

In conclusion, from to *Figure 6*, the application of machine learning to socially intelligent robots represents a transformative synergy between technology and human interaction (Lv et al., 2022). Through sophisticated algorithms and models, these robots are equipped to recognize and respond to human emotions, engage in natural language conversations, adapt their behaviour based on individual preferences, and interpret non-verbal cues (Marge et al., 2022). The integration of machine learning in the development of socially intelligent robots not only enhances their technical capabilities but also contributes to the creation of more empathetic, responsive, and adaptable machines (Singh & Chouhan, 2023).

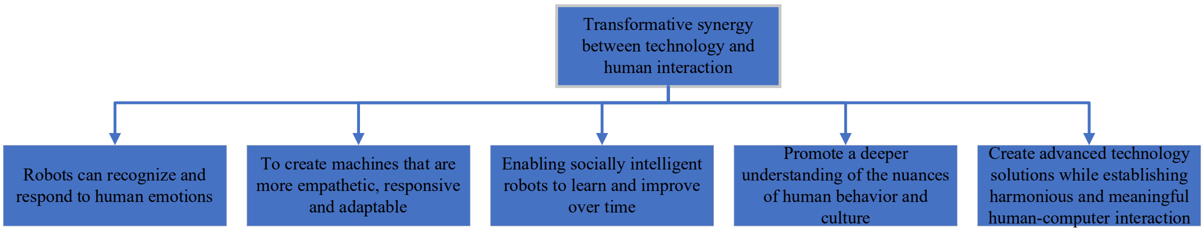

Figure 6. Transformative synergy between technology and human interaction

The use of machine learning in this context extends beyond technical proficiency to address ethical considerations. Developers strive to mitigate biases, uphold privacy standards, and ensure responsible and respectful deployment of these robots in diverse social environments (Schwartz et al., 2022). The continuous evolution of machine learning techniques enables socially intelligent robots to learn and improve over time, fostering a deeper understanding of human behaviour and cultural nuances (Benvenuti et al., 2023).

As socially intelligent robots become more prevalent in sectors such as healthcare, education, and customer service, the careful application of machine learning principles becomes paramount (Vermesan et al., 2022). The goal is not only to create advanced technological solutions but also to establish harmonious and meaningful human-robot interactions (F. Zhang et al., 2022). With ongoing research and advancements in machine learning, the future holds the promise of socially intelligent robots that seamlessly integrate into society (Singh & Chouhan, 2023), providing valuable support, companionship, and assistance while adhering to ethical standards and societal norms.

ACKNOWLEDGMENT

We thank all the anonymous reviewers for their hard reviewing work.

FUNDING

This research did not receive any grants.

CONFLICT OF INTEREST

The author declares there is no conflict of interest regarding this paper.

DATA AVAILABILITY STATEMENT

There is no data associated with this paper.

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