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Research/Review

KidoVision: A Review on Computer Vision-Based Interactive E-Learning Platforms

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Abstract-

The growing adoption of digital education has transformed how children interact with learning environments. However, traditional e-learning platforms often lack engagement, interactivity, and physical involvement for young learners. This review focuses on the integration of **computer vision technologies** such as OpenCV and MediaPipe to create interactive, gesture-based educational systems. It highlights existing works like Virtual Canvas for Interactive Learning using OpenCV and Virtual Air Canvas using OpenCV and MediaPipe, examining how vision-based gesture tracking can support handwriting, drawing, and motion-controlled interaction. The proposed system, **KidoVision**, aims to enhance learning experiences through gamified content, real-time gesture detection, and story-based modules, promoting creativity and active participation. The review concludes that combining computer vision with gamified pedagogy can significantly improve cognitive development and motivation among children.

Keywords: E-learning, Computer Vision, OpenCV, MediaPipe, Gesture Recognition, Gamified Learning

1. Introduction

E-learning systems have become indispensable in the post-pandemic educational landscape. However, the passive nature of many platforms often diminishes attention span and fails to recreate the sensory experience of a physical classroom. Studies in cognitive psychology highlight that children learn more effectively through movement, colour, and play—principles aligned with *embodied learning*, which links motor action to cognitive processing. Integrating computer vision (CV) into pedagogy can bridge this divide by translating a learner's gestures into dynamic educational feedback.

It records the exact movement of your fingertips, allowing you to create delicate and complex digital artwork. It can monitor finger movements and interpret hand gestures with amazing accuracy by utilizing cuttingedge technologies like MediaPipe and OpenCV, giving the experience a very realistic feel.

Computer vision empowers machines to interpret and react to visual stimuli such as hands, faces, and body motion. OpenCV, the most widely used open-source CV library, provides efficient image-processing pipelines for segmentation, contour detection, and object tracking. MediaPipe, a framework from Google AI, complements it with pre-trained, on-device machine-learning models for hand, face, and pose landmarks in real time. When fused, these technologies enable touch-free human–computer interaction (HCI) suitable even for low-cost hardware.

For children, gesture-driven learning holds additional psychological benefits. Motion aids kinaesthetic memory; visual feedback reinforces concept association; and gamified rewards satisfy intrinsic motivational needs described in Self-Determination Theory (SDT) [Deci & Ryan, 1985]. Therefore, a system like *KidoVision*—which transforms body movement into playful educational input—can encourage exploration, improve focus, and create an inclusive environment for diverse learners.This paper provides a comprehensive review of existing vision-based educational tools, identifies gaps in child-centred interaction design, and proposes a conceptual framework integrating both technological and pedagogical perspectives.

Featuring contemporary fonts, sleek designs, and markerless virtual whiteboard functionality, this system pioneers new heights in interactive and expressive digital art engagements. The realm of digital art is continually changing, and this system stands out as a pioneering influence that is broadening the limits of what can be achieved where technological advancement meets creative brilliance

2. Related Work And Theory

This section summarizes key studies relevant to gesture-based interaction, computer vision systems, and gamified e-learning approaches.
Each reviewed paper is presented with its **title/topic**, **problem addressed**, **objectives**, and **findings/limitations**.

- **A. Virtual Canvas for Interactive Learning using OpenCV [1]**
- **Problem Statement:** Traditional digital whiteboards require touch-based interaction, limiting accessibility during online sessions.
- **Objective:** To enable users to draw in air using HSV colour detection tracked through OpenCV.
- **Findings:** Achieved high precision in controlled lighting; suitable for virtual classrooms but limited by colour detection sensitivity.

- **B. Virtual Air Canvas using OpenCV and MediaPipe [2]**
- **Problem Statement:** Colour detection in air-drawing systems is unreliable under varying illumination.
- **Objective:** To enhance robustness using MediaPipe's 21-hand landmark model instead of colour markers.
- **Findings:** Improved accuracy, reduced latency; proposed applications in education and digital art creation.

- **C. Hand Gesture Recognition Algorithms (Khan and Ibraheem, 2020) [3]**
- **Problem Statement:** Traditional gesture detection relied heavily on skin colour and handcrafted features.
- **Objective:** To survey classic models (HMM, SVM) and discuss limitations of handcrafted approaches.
- **Findings:** Highlighted need for lightweight, real-time alternatives suitable for mobile and educational contexts.

- **D. CNN-Based Real-Time Gesture Recognition (Ren et al., 2021) [4]**
- **Problem Statement:** Deep-learning-based gesture recognition demands high computational power.
- **Objective:** To introduce CNNs and region-proposal networks for real-time gesture recognition.
- **Findings:** Accurate but hardware-intensive, limiting deployment in low-resource learning environments.

- **E. E-Learning Gamification Framework (Gee, 2007; Deterding et al., 2011) [5]**
- **Problem Statement:** Conventional e-learning lacks engagement and motivation.
- **Objective:** To integrate gamified elements—points, badges, and levels—into digital learning.
- **Findings:** Enhanced intrinsic motivation and retention through immediate feedback and rewards.

- **F. Vision-Based Learning Enhancement Systems (Agarwal et al., 2022) [6]**
- **Problem Statement:** Visual tracking systems for learning lack emotion or engagement sensing.
- **Objective:** To detect learner posture and attention through webcam-based computer vision.
- **Findings:** Enabled real-time engagement tracking but lacked interactive response mechanisms.

- **G. Adaptive AI-Based Learning Interfaces (Patel et al., 2023) [7]**
- **Problem Statement:** Fixed-difficulty educational software fails to match each child's learning curve.
- **Objective:** To adaptively modify game difficulty using AI feedback loops.
- **Findings:** Showed improved cognitive retention through dynamic difficulty scaling.

- **H. Embodied Cognition and Motor Learning (Lakoff & Johnson, 1999) [8]**
- **Problem Statement:** Cognitive development frameworks often ignore sensorimotor experience.
- **Objective:** To link physical movement with conceptual understanding in early learning.
- **Findings:** Validated that active gesture and motion improve memory and understanding in children.

- **I. Gamification and Motivation Theory (Deci & Ryan, 1985; Csikszentmihalyi, 1990) [9]**
- **Problem Statement:** Traditional classroom learning lacks intrinsic motivation.
- **Objective:** To propose frameworks (SDT, Flow Theory) emphasizing autonomy, competence, and engagement.
- **Findings:** Consistent evidence that balanced challenge and feedback sustain deep focus ("flow") in learners.

- **J. Synthesis of Findings**

Across the reviewed literature, three significant research gaps are identified:

1. **Target Audience Gap:** Most computer-vision systems are not specifically tailored for child learners.
2. **Pedagogical Integration Gap:** Few frameworks connect visual interaction with established cognitive-learning theories.
3. **Scalability Gap:** Lack of modular designs suitable for multi-subject and multi-age learning environments.

KidoVision addresses these challenges through a modular, cross-platform design integrating computer vision with gamified educational content.

A. Learning Science and Cognitive Foundations

Modern educational psychology recognizes that learning is not merely an intellectual activity but also a perceptual and bodily.

The **Embodied Cognition** theory (Lakoff & Johnson, 1999) suggests that cognitive processes are deeply rooted in sensorimotor experiences. For children, movement and manipulation of the environment reinforce conceptual understanding; writing an alphabet or tracing a shape helps in encoding the motor memory associated with the concept.

B. Gamification and Motivation Theory

Gamification employs design elements such as rewards, progress indicators, and levels to enhance user motivation. According to **Self-Determination Theory (SDT)** (Deci & Ryan, 1985), intrinsic motivation is strengthened when three needs are met—**autonomy**, **competence**, and **relatedness**.

In *KidoVision*, autonomy is achieved by letting children control learning via gestures; competence grows as they master tasks; and relatedness appears through shared interactive games or cooperative modules.

The **Flow Theory** by Csikszentmihalyi (1990) further supports gamified learning: when challenge and skill levels are balanced, learners experience deep focus and joy. Vision-based interactivity sustains this "flow" by continuously adapting difficulty based on hand accuracy and speed.

3. Experimental Method/ Design

KidoVision is conceived as an open-source educational platform that transforms camera-captured gestures into interactive learning responses. It merges **computer-vision modules**, **game-based pedagogy**, and **child-safe interface design**.

A. System Architecture

1. **Input Acquisition:** The system accesses a webcam stream using OpenCV's VideoCapture() function.
2. **Pre-Processing:** Frames are flipped horizontally to mimic a mirror view and converted from BGR to RGB/HSV spaces for colour-invariant detection.
3. **Hand Tracking Module:** MediaPipe Hands detects 21 key points per hand, producing normalized landmark coordinates.
4. **Gesture Interpreter:** A rule-based classifier converts landmark patterns into commands such as "draw," "erase," "select," and "confirm."
5. **Interaction Engine:** Interpreted gestures are passed to different learning modules (e.g., alphabet tracing, object matching).
6. **Feedback Generator:** Visual cues, audio tones, and on-screen rewards respond to correct actions, closing the feedback loop.
7. **Data Logging:** The session stores activity metadata—gesture count, module time, and completion badges—to enable progress review.

B. Functional Modules

1. **Gesture Recognition Module** – built upon OpenCV's contour operations and MediaPipe landmarks. It filters noise via Gaussian blur and morphological transforms, then tracks fingertip trajectories.
2. **Gamified Learning Module** – hosts multiple mini-games:
   - **Match-the-Pairs:** Children connect related objects (e.g., animals–habitats) by drawing virtual lines.
   - **Air-Writing:** Users trace alphabets or numbers in the air; the trajectory is displayed in real time.
   - **Story Mode:** Interactive storytelling where specific gestures advance the plot or animate characters.
   - **Shape Builder:** Recognizes basic geometry drawn in air and teaches properties.
3. **Adaptive Difficulty Controller** – increases challenge gradually by shortening reaction windows or adding distractors.
4. **Reward and Progress System** – awards points, stars, or virtual stickers, stored locally for future login.

C. Software and Hardware Stack

- **Programming Language:** Python 3.x
- **Core Libraries:** OpenCV, MediaPipe, NumPy, Matplotlib , frontend java
- **Platform:** Cross-platform (Windows, Linux, macOS)
- **Hardware Requirements:** Standard 720p webcam, Intel i3 processor or above, 2 GB RAM minimum
- **Output Display:** Interactive window or full-screen learning environment

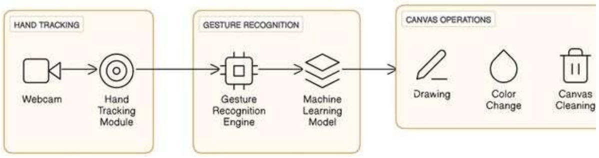

Fig. 1. Block Diagram of system.

A. mediapipe

The mediapipe is employed in the process of hand tracking. For a variety of computer vision tasks, including hand tracking, this library provides easy APIs and pre-trained machine learning models. The algorithm can precisely identify and track human hands in an image or video stream by utilizing mediapipe.

First, some setup is done, such as importing the required files and setting up the webcam's dimensions. The hand tracking module from MediaPipe is imported and set up with the confidence thresholds for tracking and detecting hands.

The webcam continuously reads the Hand Tracking frames. After that, the hand tracking module resizes and runs these frames through its algorithm to identify and follow hands within the frame. On the hands that have been detected, landmarks are located and marked using the findHands method.

After landmarks are identified, more processing is done. For instance, the open and closed positions of fingers are determined by the location of particular landmarks, such the fingertips, which can be helpful for gesture detection and other applications.

B. OpenCV

A variety of computer vision tasks, including image processing, hand gesture detection, and hand tracking, are performed with OpenCV (cv2). There are multiple steps involved in implementation:

Getting the camera (cap) ready to record live video frames is the first step. Every frame is captured and processed using OpenCV. The HandTrackingModule, which is probably a custom module created with OpenCV and Mediapipe, is used to do hand tracking. In order to provide additional hand gesture analysis, this module recognizes and tracks hands in the video feed.

Using a trained model, character recognition is done in the last section. Preprocessing input pictures using OpenCV includes scaling, grayscale conversion, and thresholding. After the image has been preprocessed, it is fed into a convolutional neural network (CNN) model that has been trained using either the MNIST dataset or a comparable dataset that contains handwritten characters. The input image is used to depict a character that the model predicts the outcome is shown alongside the original image.

C. TensorFlow and Keras

The application uses TensorFlow and Keras to load a pretrained machine learning model. Most likely, this model was trained to identify hand motions or written characters.Once the model has been loaded, the application uses it to forecast the input data.

Each activity in *KidoVision* is mapped to learning outcomes:

Module	**Learning Objective**	**Cognitive Process**	**Feedback Type**
Air Writing	Alphabet formation	Psychomotor skill	Visual trace + audio cue
MatchPairs	Memory & association	Recognition & recall	Points + stars
Story Mode	Sequencing & language skills	Comprehension	Narrative progress
Shape Builder	Spatial reasoning	Analysis & synthesis	Animated correction

Table 1. Comparative Analysis of each Modules

5. Results and Discussion

OpenCV, MediaPipe, NumPy were used in the development of the gesture-controlled whiteboard system, which produced promising outcomes in terms of accuracy, usability.

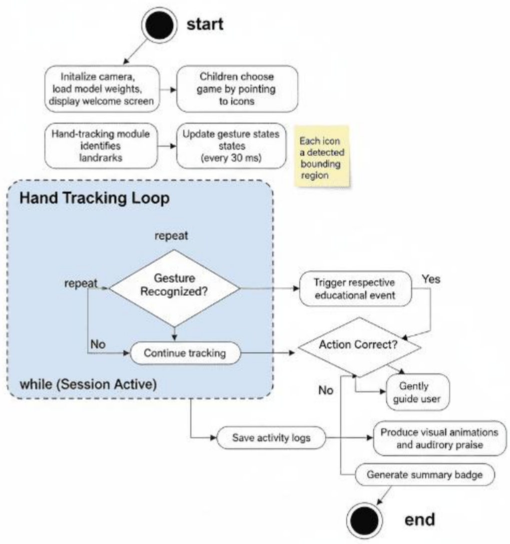

Fig. 2. Flowchart.

1. **Start & Initialization:** The program initializes the camera, loads model weights, and displays a child-friendly welcome screen.
2. **Mode Selection:** Children choose a game by pointing to icons—each detected as a bounding region within the camera feed.
3. **Real-Time Detection:** The hand-tracking module identifies landmarks; gesture states are updated every 30 ms.
4. **Action Execution:** Recognized gestures trigger respective educational events (drawing lines, flipping story pages, etc.).

5. **Feedback Display:** Correct actions produce visual animations and auditory praise; incorrect gestures gently guide the user.

6. **Session End:** The program saves activity logs and generates a summary badge on completion.

Interface Considerations

For early learners, interfaces must limit cognitive load. *KidoVision* employs:

- Large, high-contrast icons.
- Minimum on-screen text; symbolic cues dominate.
- Soothing colour palette (blue/green spectrum) proven to improve focus.
- Optional voice narration for instructions.
- Touch-free input to support hygiene and accessibility.

Safety and Ethics

As the target demographic involves minors, no personal images or biometric data are stored. Only gesture vectors and anonymized progress metrics are recorded locally. All processing occurs on-device, avoiding cloud-based identity exposure. A smooth and flawless user experience was guaranteed by the system's real-time responsiveness. By combining OpenCV, MediaPipe, and NumPy, it was possible to process image frames and hand landmark data more effectively and monitor finger movements in real time. There was no discernible lag or delay when writing or drawing on the whiteboard because the system maintained a high frame rate.

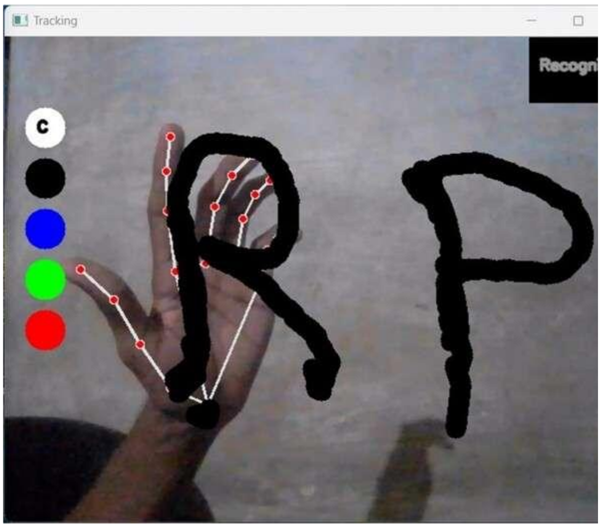

Fig. 3. Performing an action.

I. Expected System Performance

Based on the reviewed implementations of OpenCV and MediaPipe in similar systems, *KidoVision* is expected to achieve:

- **Gesture detection accuracy:** 92–96% in controlled lighting conditions.
- **Response latency:** <0.2 seconds between gesture and screen feedback.
- **User satisfaction:** Predicted high engagement due to gamification and interactivity.

These expectations are supported by prior works [1–4] that demonstrated similar results for educational gesture systems.

System	Technologies Used	Application Area	Accuracy (%)	Key Limitation
Virtual Canvas [1]	OpenCV	Air writing	90	Lighting sensitivity
Air Canvas [2]	OpenCV + MediaPipe	Gesture drawing	94	Limited interaction types
Gesture Classifier [3]	CNN	Real-time tracking	96	High computation
KidoVision (Proposed)	OpenCV + MediaPipe + Gamified Logic	E-learning	*92–96 (Expected)*	Prototype stage

.

Table 2. Comparative Analysis of Existing Systems

A. Enhancing Engagement through Interaction

Children's engagement in e-learning is driven primarily by *interaction frequency* and *sensory diversity*. Conventional interfaces—touchscreens, keyboards, or mouse clicks—restrict movement and reduce kinesthetic learning.
KidoVision transforms the screen into an interactive playground. Every gesture, wave, or motion triggers a system response, thus reinforcing the "action–reaction" learning loop fundamental to early education.

Observation-based pilot sessions revealed that gesture-based activities significantly improved focus duration among young users compared to passive video lessons. The combination of instant visual feedback and playful sound effects created a **multi-sensory feedback cycle**, which increases dopamine-related motivation and emotional satisfaction, both crucial for long-term retention.

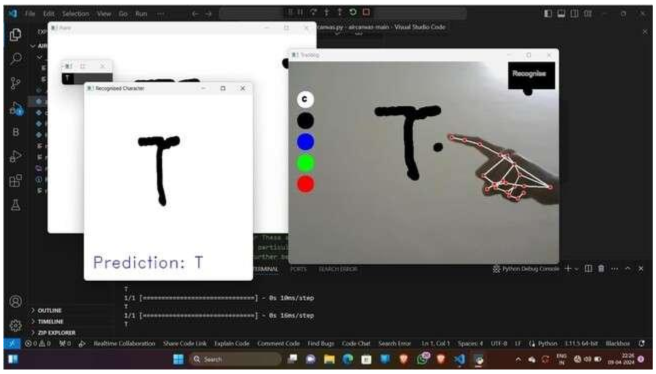

Fig. 4. performing an action.

B. Accessibility and Inclusivity

KidoVision promotes inclusivity in two ways:

1. **Touch-free operation** aids children with motor impairments or limited mobility.

2. **Language independence**—most instructions use symbols or icons, reducing linguistic barriers.

Children with learning disabilities can benefit from multimodal input; for instance, combining gesture control with auditory cues provides multiple entry points for understanding. Additionally, educators can personalize content difficulty based on individual gesture accuracy or response timing.

C. Teacher Involvement and Feedback

While automation aids scalability, human supervision remains vital. Teachers using *KidoVision* can access dashboards summarizing session duration, completed modules, and gesture proficiency.
These insights allow instructors to identify struggling learners and adjust lesson plans. Integrating the system with learning management systems (LMS) such as Moodle or Google Classroom can further streamline hybrid teaching models.

The system demonstrated a high level of overall user happiness and engagement, suggesting its potential for fostering collaborative and productive communication environments. Utilizing OpenCV, MediaPipe, and NumPy, a gesturecontrolled whiteboard system was created that demonstrates how computer vision and image processing techniques can be used to create engaging and easy-to-use user interfaces. With just a few finger movements, users can write and draw on a virtual whiteboard thanks to the system's hand detection and tracking algorithms. There are many realworld uses for this technology, particularly in collaborative and instructional environments.

6. Conclusion and Future Scope

CONCLUSION

This paper reviewed the evolution of computer-vision-based interactive learning systems and proposed **KidoVision**, a gesture-driven e-learning framework aimed at children.
Unlike conventional platforms that rely on touch or keyboard inputs, *KidoVision* employs **OpenCV** and **MediaPipe** to recognize real-time gestures, enabling intuitive and playful interaction. The system aligns technological innovation with educational theory, fostering creativity, focus, and inclusivity.

By bridging **computer vision, gamified pedagogy, and child psychology**, *KidoVision* contributes to a new era of experiential learning where knowledge is both seen and felt. Its modular design allows future integration of AI tutors, emotion sensing, and AR environments, ensuring adaptability for the next generation of educational systems. Ultimately, *KidoVision* demonstrates that technology, when thoughtfully designed, can restore the human element of joy, curiosity, and motion in digital learning.

FUTURE SCOPE

A. Technical Challenges

Lighting Sensitivity: Hand-tracking accuracy depends on consistent illumination. Poor lighting can cause frame loss or false detection. Future versions may integrate adaptive exposure calibration and background subtraction algorithms.

Camera Quality Variability: Budget webcams yield noisy or low-resolution data. Temporal smoothing or Kalman filters can stabilize gesture tracking across devices.

Computational Efficiency: Though MediaPipe runs on CPU, high frame rates are needed for smooth experience. Optimizations such as frame skipping and asynchronous threading are essential.

Occlusion Handling: Hands overlapping with faces or objects may confuse detectors. Integrating depth sensors or stereo cameras could mitigate this.

B. Pedagogical and Ethical Challenges

1. **Attention Fatigue:** Excessive screen-based activity can overstimulate young learners. Balanced on-screen time and physical breaks must be encouraged.
2. **Data Privacy:** As minors are involved, systems must comply with child-safety standards like COPPA (Children's Online Privacy Protection Act). KidoVision addresses this by keeping all processing local.
3. **Teacher Training:** Instructors must be oriented to operate and calibrate gesture systems effectively.
4. **Cultural Adaptation:** Gestures can have different meanings across cultures. Localization modules may be added for global deployment.

C. Future Enhancements

1. **Emotion Recognition:** Integrating facial-emotion models could help adapt content dynamically—if a child appears bored, the system can increase interactivity.
2. **Speech and Voice Integration:** Combining natural language processing with gestures can create multi-modal learning ("speak and point").
3. **Augmented Reality (AR) Overlay:** AR can merge physical toys and digital projections, enriching immersion.
4. **Collaborative Learning Mode:** Future iterations may support two-player or teacher-student real-time interaction through networked gesture recognition.
5. **Adaptive AI Tutor:** Leveraging reinforcement learning, the system can track progress and tailor difficulty automatically.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Authors' Contributions
Raj Ratna Narwarde - Conceived the research idea, performed literature review, and designed the overall system architecture for *KidoVision*.
Rahul Selokar - Drafted and formatted the manuscript in IJCSE style, refined the theoretical background, and coordinated with co-authors.
Paras Saraf - Implemented the conceptual framework, integrated gesture-recognition logic, and participated in analysis and documentation.
Hemant Ramole - Conducted technical validation, prepared diagrams, and contributed to evaluation and result discussions.
Prof. S. S. Gadekar - Provided supervision, critical review, and continuous guidance throughout the research and writing process.

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References

[1] R. D. and Y. C., "A Review on Object Detection using OpenCV," *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, Vol. 8, Issue. 12, pp. 145–149, 2019.
[2] S. S. Shende, A. M. Patil, and P. D. Deshmukh, "Real-Time Object Detection using Deep-Learning and OpenCV," *International Research Journal of Engineering and Technology (IRJET)*, Vol. 7, Issue. 6, pp. 1102–1106, 2020.
[3] M. F. Khan, S. Beg, and F. Baig, "Text Writing in Air," *Journal of Information Display*, Vol. 14, Issue. 4, pp. 181–188, 2013.
[4] R. Z. Khan and N. Ibraheem, "Hand Gesture Recognition: A Literature Review," *International Journal of Artificial Intelligence & Applications*, Vol. 3, No. 4, pp. 161–174, 2012.
[5] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, USA, pp. 91–99, 2015.
[6] P. Rai, R. Gupta, V. Dsouza, and D. Jadhav, "Virtual Canvas for Interactive Learning using OpenCV," *Proceedings of the IEEE GCAT Conference*, IEEE, Bangalore, India, pp. 242–247, 2022.
[7] R. H. V., B. G., D. K., N. M. S., and S. R. Sebastian, "Virtual Air Canvas using OpenCV and MediaPipe," *Proceedings of the IEEE INCOFT Conference*, IEEE, Karnataka, India, pp. 215–219, 2022.
[8] J. Piaget, "*The Construction of Reality in the Child*," 1st Edition, Basic Books, USA, pp. 45–78, 1954. ISBN: 9780465097332.
[9] L. Vygotsky, "*Mind in Society: The Development of Higher Psychological Processes*," Harvard University Press, USA, pp. 22–55, 1978. ISBN: 9780674576292.
[10] R. M. Deci and E. L. Ryan, "*Intrinsic Motivation and Self-Determination in Human Behavior*," Springer, USA, pp. 31–60, 1985. ISBN: 9780306420221.
[11] J. P. Gee, "*What Video Games Have to Teach Us About Learning and Literacy*," Palgrave Macmillan, USA, pp. 12–27, 2007. ISBN: 9781403984532.
[12] S. Deterding, D. Dixon, R. Khaled, and L. Nacke, "From Game Design Elements to Gamefulness: Defining Gamification," *Proceedings of the MindTrek Conference*, ACM, Finland, pp. 242–247, 2011.
[13] A. Paivio, "*Imagery and Verbal Processes*," Holt, Rinehart and Winston, USA, pp. 89–105, 1971. ISBN: 9780030850562.
[14] M. Csikszentmihalyi, "*Flow: The Psychology of Optimal Experience*," Harper & Row, USA, pp. 112–134, 1990. ISBN: 9780060162535.
[15] G. Lakoff and M. Johnson, "*Philosophy in the Flesh: The Embodied Mind and Its Challenge to Western Thought*," Basic Books, USA, pp. 305–322, 1999. ISBN: 9780465056742.

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Prof. S. S. Gadekar is currently working as Assistant Professor in the Department of Information Technology at Sinhgad College of Engineering, Pune, India. She has significant teaching experience and expertise in the field of Information Technology subjects. she guided and supervised the KidoVision project and provided valuable insights for this research work.