





Empowering Educators, Engaging Students

We use computer vision to reignite students' passion for learning. By delivering actionable insights, we empower educators to enhance learning experiences and drive meaningful interactions.



The Attention Crisis in Education

Attention is the Foundation of Learning—And It's Slipping Away



Educators

Educators struggle to keep students focused and lack real-time insights into participation and comprehension.



Students

Students today are bombarded with distractions, leading to shorter attention spans and lower engagement.



Educators: Overworked, Under-Resourced, and Searching for Solutions

Educators aren't just teachers anymore—they're content creators, tech troubleshooters, and engagement managers, all at once.



70% of teachers report feeling overwhelmed by the need to keep students engaged.



Limited real-time feedback makes it impossible to know if students are following along.



Manual engagement tracking (surveys, quizzes) is outdated, reactive, and impractical at scale.



Students: A Generation of Learners Struggling to Stay Engaged and Focused

For students, learning is more fragmented than ever. Attention spans are shrinking, with many struggling to succeed in the current educational environment.



72% of students say they find it hard to concentrate in class due to distractions.



Student attention spans are declining, affecting comprehension and retention.

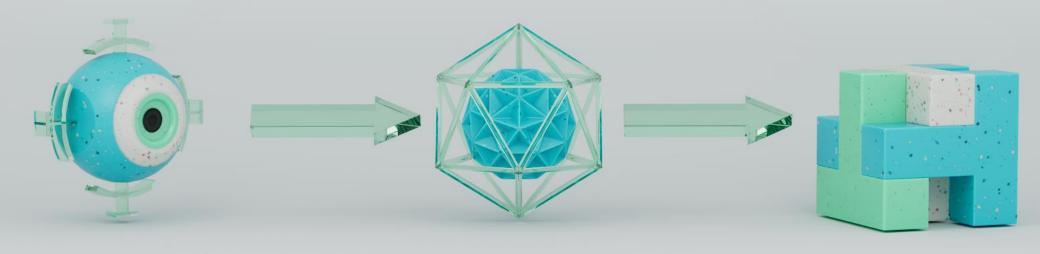


Traditional tools (tests, surveys) are reactive, not proactive.



From Data to Action: Understanding Engagement in Real Time

NEXI transforms classroom behavior into actionable insights. Our AI-powered system follows three key steps: Capture, Analyze, and Recommend.



Capture

Al-powered cameras analyze student engagement (eye contact, posture, expressions).

Analyze

Machine learning processes real-time data to measure comprehension & participation.

Report

Teachers receive actionable insights on how to adapt lessons.



Seeing What Matters: Turning Classroom Behavior into Data

Our system passively observes engagement signals—eye contact, posture, participation—without disrupting the learning experience.

- Tracks real-time student behaviors with Al-powered computer vision.
- Measures engagement through non-intrusive analysis of focus levels.
- Works across in-person, hybrid, and virtual classrooms.





From Noise to Knowledge: Al That Understands Learning Engagement

Not all attention is created equal. NEXI's AI filters meaningful engagement signals and discards noise.



Real-time focus recognition & behavioral analysis refine engagement scores.



Adaptive machine learning recognizes patterns over time to improve accuracy.



Adjusts for individual student behavior baselines for fairness.





Actionable Insights That Empower Both Educators & Students

Data is useful when it leads to action. NEXI delivers practical, easy-to-use insights for educators & students.



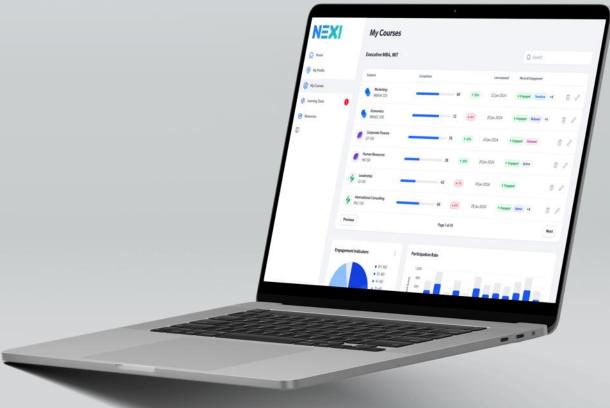
Instant feedback dashboards show areas where students disengage.



Smart recommendations suggest teaching adjustments to keep students engaged.



Integrates with existing learning management systems (LMS) for seamless implementation.





Hardware

Cameras



All-round camera

It does the job

Specialized camera

More pixels to work with

Modular specialized camera

More pixels to work with and a smaller footprint



Hardware

Processing units



"Mini" computer

Large footprint

Mini computer

Small footprint

NEXI Spider

Smaller foot print and modularity





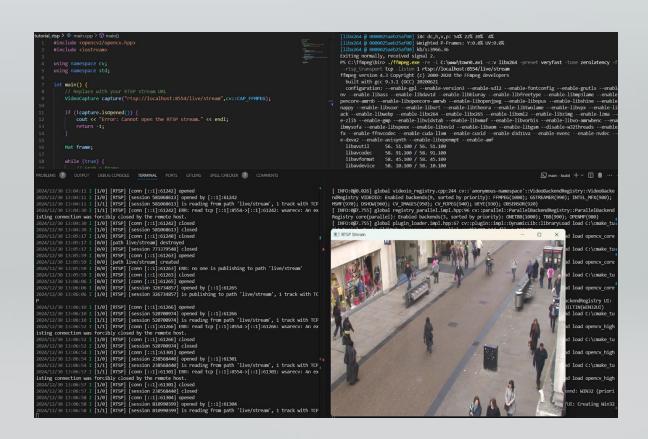
OpenCV (Open Source Computer Vision Library) is a **free**, **open-source software library** designed for real-time computer vision and machine learning applications.

Initially developed by Intel, OpenCV provides a comprehensive infrastructure for building computer vision systems and is widely used in both **research and commercial products**.

The library contains **over 2,500 algorithms** for tasks such as **image and video processing,** object detection, image segmentation, facial recognition, and more.

OpenCV supports multiple programming languages - including C++, Python, Java, and MATLAB-and runs on major operating systems like Windows, Linux, macOS, Android, and iOS.

Its efficiency and modular design make it especially suitable for real-time applications, and it is considered the **de facto standard tool in the computer vision industry**.



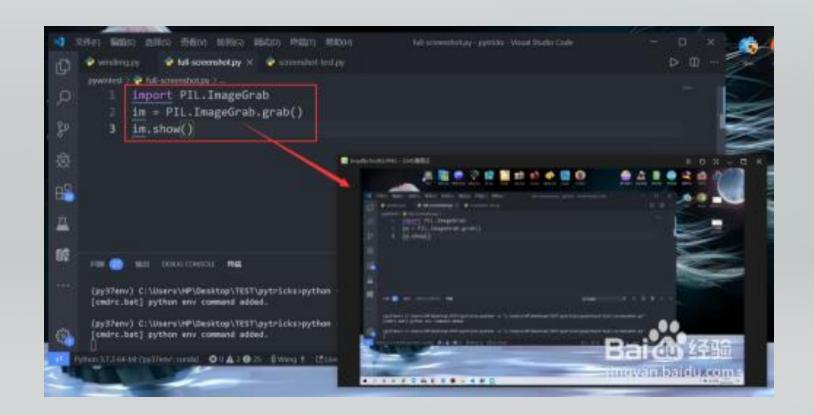




The Python Imaging Library adds **image processing capabilities** to your Python interpreter.

This library provides extensive file format support, an efficient internal representation, and fairly powerful image processing capabilities.

The core image library is **designed for fast access to data stored** in a few basic pixel formats. It should provide a solid foundation for a general image processing tool.





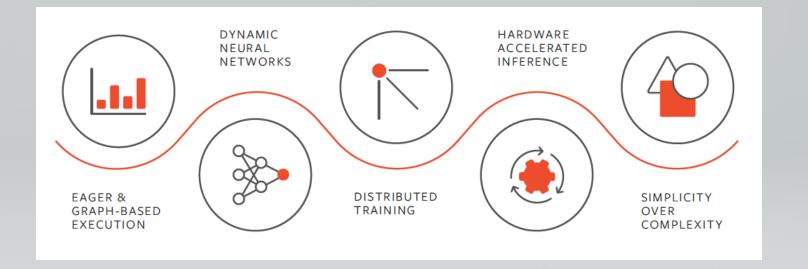


PyTorch is an **open-source machine learning library** based on Python and the Torch library, developed by Meta AI.

It is **widely used** for building and training deep learning models, especially in fields like computer vision and natural language processing.

PyTorch is popular because it offers:

- An easy-to-use Python interface and dynamic computation graphs for flexible model development;
- Strong support for GPU acceleration, enabling faster training of neural networks;
- Applications in AI research, prototyping, and production, including tasks like image classification, NLP, and reinforcement learning.



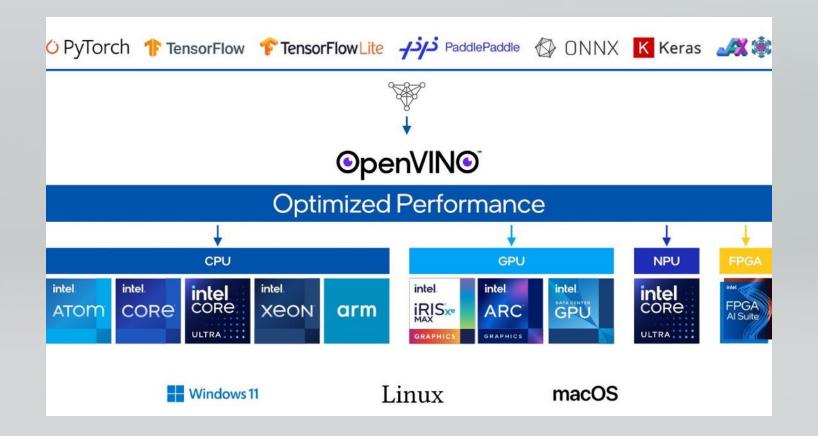


OpenVINO

OpenVINO is an open-source toolkit developed by Intel for optimizing and deploying Al models-especially computer vision and deep learning models-across a wide range of Intel hardware (CPUs, GPUs, VPUs, FPGAs, and edge devices).

It enables fast, **efficient inference** by converting and optimizing models from **popular frameworks like TensorFlow and PyTorch**, supporting a "write-once, deploy-anywhere" workflow.

OpenVINO is **widely used** in applications such as real-time video analytics, retail analytics, industrial inspection, smart cities, and healthcare imaging, making it easier to build scalable, highperformance AI solutions on Intel platforms





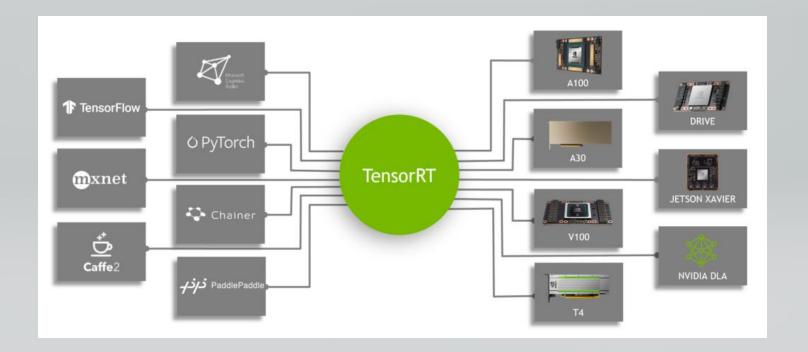


NVIDIA® TensorRT[™] is an **ecosystem of tools** for developers to achieve **high-performance deep learning inference**.

TensorRT includes inference **compilers**, **runtimes**, **and model optimization**s that deliver low latency and high throughput for production applications.

The TensorRT ecosystem includes the TensorRT compiler, TensorRT-LLM, TensorRT Model Optimizer, and TensorRT Cloud.

TensorRT is widely used in industries such as autonomous vehicles, healthcare, robotics, and large-scale Al services, making it essential for efficient, production-ready Al on NVIDIA hardware.







VS



Quantization

Reduces model precision (e.g., from FP32 to INT8) to speed up inference and lower memory usage.

Pruning/Sparsity

Removes unimportant weights or neurons, making the model smaller and faster.

Layer Fusion

Combines consecutive operations (like convolution and activation) into one for more efficient execution.

Kernel Auto-Tuning

Automatically selects the best computation methods for the hardware to maximize performance.

Memory Management

Optimizes how data is stored and accessed during inference to improve speed and efficiency.

Performance Tuning

Adjusts settings to optimize for either lower latency or higher throughput, depending on deployment needs.

Model Compression

Reduces the model's size using techniques like quantization and pruning for easier deployment.

Source Framework Support

Indicates which training frameworks (e.g., PyTorch, TensorFlow, ONNX) are compatible with the optimizer.

Target Hardware

Specifies which hardware (e.g., Intel or NVIDIA devices) the optimizations are designed for.

	OpenVINO	TensorRT	
Quantization	INT8, post-training & QAT	FP16, INT8, FP8, INT4, NVFP4, post-training & QAT	
Pruning/Sparsity	Supported (structured/unstructured)	Supported (sparsity, pruning)	
Layer Fusion	Supported	Supported	
Kernel Auto- Tuning	Limited (hardware-specific scheduling)	Advanced (auto-tuning for GPU kernels)	
Memory Management	Batch processing, multi- device, async, caching	Dynamic tensor memory management, workspace optimization	
Performance Tuning	Latency/throughput hints, device-agnostic	Precision mode, kemel selection, graph optimizations	
Model Compression	Weight compression (esp. for LLMs/VLMs)	Supported via pruning, quantization, sparsity	
Target Hardware	Intel CPUs, GPUs, VPUs	NVIDIA GPUs (data center, edge, Jetson)	



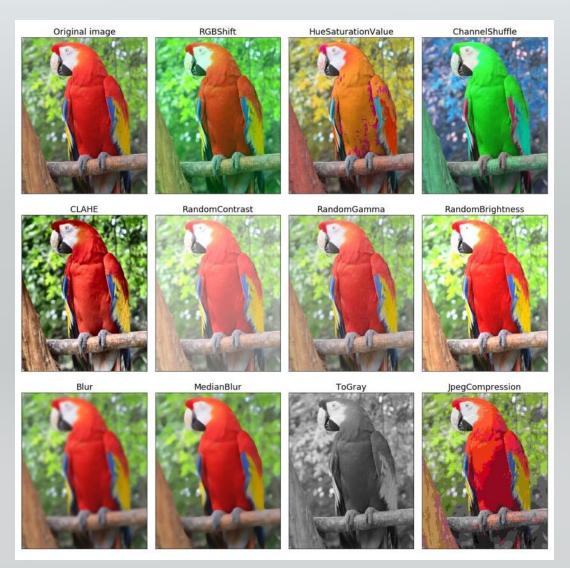
Albumentations

Image augmentation is used in deep learning and computer vision tasks to **increase the quality of trained models**. The purpose of image augmentation is to **create new training samples** from the existing data.

The library is **widely used** in industry, deep learning research, machine learning competitions, and open-source projects.

Simple, Unified API: One consistent interface for all data types - RGB/grayscale/multispectral images, masks, bounding boxes, and keypoints.

A fast, production-optimized augmentation library with 70+ high-quality transforms that integrates seamlessly with PyTorch, TensorFlow, and other deep learning frameworks.









Pandas and Polars are Python libraries for **data manipulation** and analysis, both providing DataFrame structures for handling **tabular data**.

Pandas is the most widely used library for data analysis in Python, known for its intuitive syntax and deep integration with the Python ecosystem. It is ideal for small to medium-sized datasets and is beginner-friendly, making it popular for exploratory data analysis and prototyping.

Polars is a newer, **high-performance library** built in Rust, designed for **speed**, **scalability**, **and efficient memory usage**. It excels with **large datasets**, offers parallel processing, and supports both eager and lazy execution modes for optimized computations. Polars is especially useful when working with big data or when performance is critical.

Feature	Pandas	Polars	
Performance	Moderate	High, especially for big data	
Memory Usage	High	Low (Arrow-based, chunked)	
Ease of Use	Beginner-friendly	Moderate learning curve	
Scalability	Limited	Excellent	





PostgreSQL is a powerful, **open-source object-relational database management system (ORDBMS)** known for its reliability, data integrity, and extensive feature set. It supports both traditional SQL and advanced features like **custom data types, JSON**, and geospatial data (with PostGIS), making it **highly flexible and extensible.**

PostgreSQL is used for:

- Storing and managing structured and semi-structured data;
- Powering web, mobile, and enterprise applications;
- Data warehousing and analytics;
- Applications requiring high security, scalability, and complex queries.

It is **trusted** by businesses, governments, and researchers worldwide for mission-critical data management.



SQLite is a **lightweight**, **self-contained**, **serverless SQL database engine** that requires zero configuration and stores all data in a single cross-platform file.

It is widely used as an **embedded database** in mobile apps, IoT devices, web browsers, and desktop applications due to its **simplicity**, **reliability**, **and minimal resource requirements**.

Common use cases include local data storage for applications, prototyping, data analysis, and as a file format for app data.



Person detection:

- Model based on MobileNetV2 backbone for detecting individuals in different poses and in both indoor and outdoor scenes;
- Good balance between inference speed and performance, meeting our current needs.

Person re-identification:

- Employs a whole-body image as input and outputs an embedding vector for matching image pairs, aiding in person tracking;
- Model based on the OmniScaleNet backbone;
- Good balance between inference speed and performance – currently sufficient for our Retail and Security products but requires performance improvements for sitting subjects with occlusions for our Education product.

Action recognition:

 Video Transformer approach - MobileNetV2 (7 actions) and ResNet34 (400 actions from the Kinectics dataset).

Face detection:

- MobileNetV2 backbone for detection on indoor and outdoor scenes;
- Offers good inference speed and adequate performance but needs improvement for detecting smaller (more distant) faces.

Face re-identification:

- Generates embedding vectors for matching pairs of face images, aiding in face tracking;
- Provides good inference speed and performance but may need enhancements for faces not directly facing the camera (up to profile view).

Facial landmark detection:

- Lightweight network that predicts facial landmarks (eyes, nose, mouth, eyebrows, ...) used to align faces and support other models;
- Good balance between inference speed and performance – currently answers our needs.



Head pose estimation:

- Utilizes a custom CNN architecture to output head yaw, pitch, and roll angles;
- Offers good inference speed and adequate performance but may need improvements for smaller (more distant) faces.

Gaze direction estimation:

- Employs a lightweight custom VGG-like model to output a vector indicating the direction of a person's gaze;
- Provides good inference speed and adequate performance, with potential improvements needed for smaller (more distant) faces.

Recognition of eye state:

- Uses a simple CNN architecture to determine if a person's eyes are open or closed, to track a subject's blink rate;
- Balances inference speed and performance well, meeting our current needs.

Facial expression recognition:

- A fully convolutional network to recognize five emotions: neutral, smiling, tired, admired, and frowning;
- Offers good inference speed and average performance, with a need to enhance performance by training top opensource models like HSEmotion on promising datasets such as the one from the Open Empathic project.

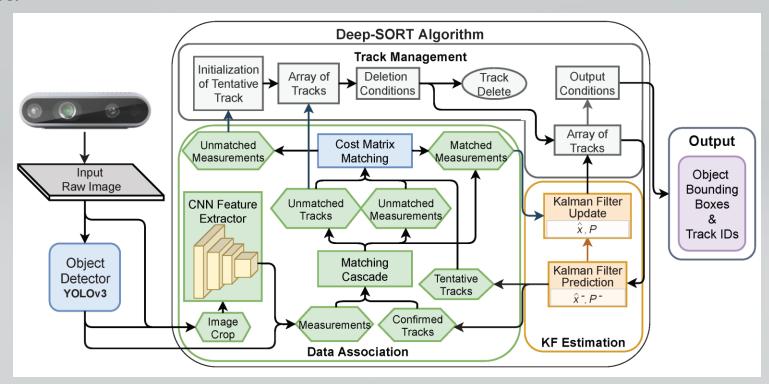
Ethnicity, gender, and age:

- Employs a triple-task custom model with a ResNet34 backbone to identify a person's ethnicity, gender, and age;
- In addition to other datasets, the model was trained on the FairFace dataset, allowing it to be substantially more accurate on novel datasets (out of distribution data) and consistent across ethnicities and gender groups;
- Balances inference speed and performance well, with ongoing improvements and potential integration with other specialized models.



Tracking

DeepSORT enhances the SORT algorithm by integrating a deep association metric for appearance-based object matching, improving occlusion handling and reducing identity switches. It combines Kalman filters for motion prediction with CNN-extracted appearance features, making it effective for surveillance and autonomous vehicles.





Tracking

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OC-SORT focuses on **crowded scenes and non-linear motion** by revising Kalman filter limitations. It uses observation-centric updates for better track recovery and **remains efficient** (real-time, online). Later versions like **Deep OC-SORT add appearance features** for enhanced performance.

ByteTrack prioritizes retaining low-confidence detections (e.g., occluded objects) via a two-stage association process. It achieves higher accuracy (77.3% MOTA) and speed (171 FPS) than SORT/DeepSORT in highway scenarios, balancing precision and computational efficiency.

OmniTrack specializes in panoramic (360°) tracking, addressing distortions like geometric deformation. It introduces Tracklet Management for temporal cues and a CircularState Module for distortion mitigation, achieving state-of-the-art results on several datasets.

Algorithm	Key Innovation Strengths		
DeepSORT	Appearance + motion fusion	Robust to occlusions, ID stability	
OC-SORT	Observation-centric updates	Crowded scenes, non- linear motion	
ByteTrack	Low-confidence detection reuse	High speed/accuracy balance	
OmniTrack	Panoramic distortion handling	stortion Wide FOV, motion robustness	



Clustering

K-means: Clusters numerical data using means and Euclidean distance.

K-modes: Handles categorical data via modes and matching dissimilarity.

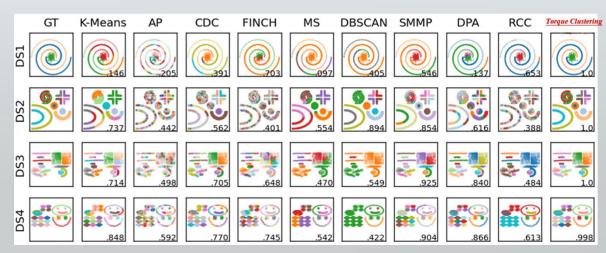
K-prototypes: Merges K-means/K-modes for mixed data. Combines Euclidean and categorical dissimilarity.

Torque Clustering: Groups numerical data by minimizing rotational torque (angular/directional relationships). Detects non-spherical shapes and resists outliers (e.g., sensor data analysis).

Key Differences:

Data Type: K-means/Torque (numerical), K-modes (categorical), K-prototypes (mixed).

Outlier Robustness: Torque > K-means.



Adjusted Mutual Information (AMI) - evaluates how well the clusters produced by each algorithm match the ground truth clusters, with a value of 1.0 indicating perfect agreement.

Algorithm	Data Type	Centroid Type	
K-means	Numerical	erical Mean	
K-modes	Categorical	Mode	
K-prototypes	Mixed	Mean/Mode	
Torque	Numerical	Torque-optimized	



Engagement Score

Multi-Modal Student Monitoring Model

1. Data Labeling

- **Define labels:** Target outcomes based on classroom behavior (1 10).
- II. Annotation: Consistently tag all data types (numeric, categorical, images) with the same label per timestamp.

2. Preprocessing

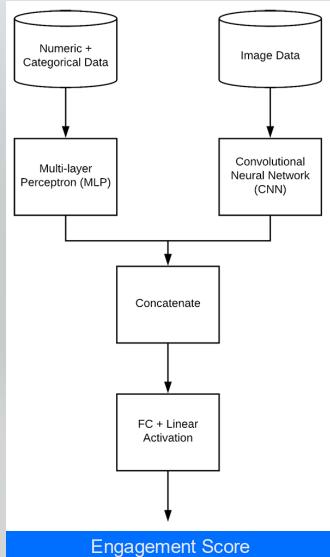
- Numeric: Normalize (gaze direction, head pose, blink rate, etc).
- **Categorical:** Encode (facial expressions, action, etc).
- III. Images: Resize, normalize pixels, and augment (flips, rotations, blur, brightness).

3. Model Design

- Multi-branch architecture:
 - MLP for numeric/categorical data.
 - ii. CNN for image analysis.
- II. Fusion layer to combine features before final prediction.

4. Training & Validation

- Use labeled data to train all branches simultaneously.
- Validate with time-synced student data to ensure alignment.







Engagement Score

Data labelling



Surveys

Help Us Improve While Helping the Planet 🔭



Thank you for participating in our user engagement surveys!

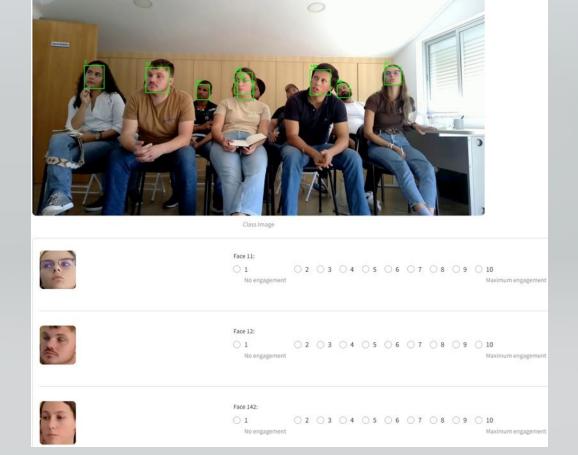
Your feedback is essential to improve the learning experience and develop better, more adaptive environments for students.

Special Contribution: 1 Tree for Every 10 Surveys!

For every 10 surveys completed, a tree will be planted as part of our partnership with the Saving the Amazon initiative.

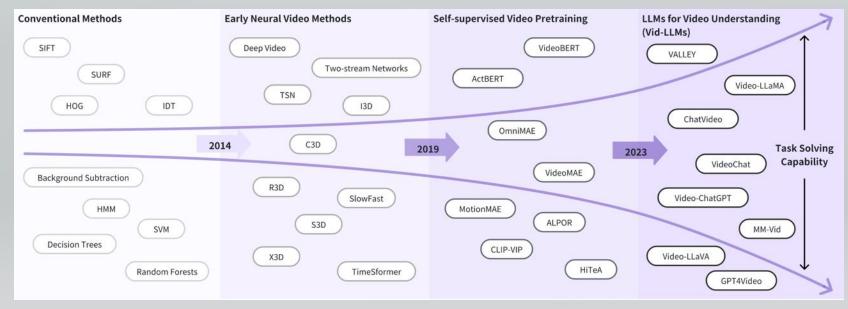
- What does the adoption of your tree include?
- a A photograph of your planted tree, labeled with the name of your choice on a biodegradable stencil.
- Planting coordinates and GPS geolocation.
- A digital donation certificate accrediting your contribution to the project.
- A digital letter with information about your tree and the community that planted it.
- You can also use the Saving the Amazon app to track the location of your tree using the code found on its label.

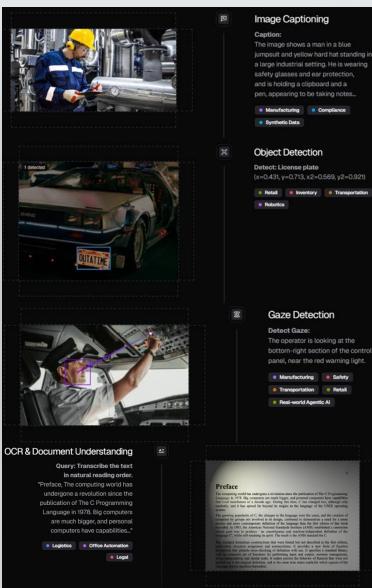
Let's grow a better future together — one survey at a time!





Vision Language Models (VLMs)

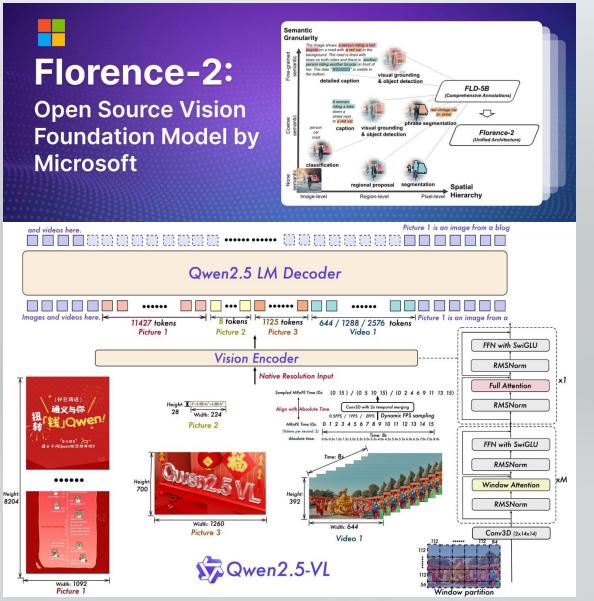






Vision Language Models (VLMs)

Rank 🔺	Method 🔺	Param (B)	Language Model
1	SenseNova-V6- Pro		
2	Gemini-2.5-Pro		
3	InternVL3-78B	78.4	Qwen2.5-72B
4	InternVL3-38B	38.4	Qwen2.5-32B
5	Step-1o		
6	SenseNova		
7	InternVL2.5- 78B-MPO	78	Qwen-2.5-72B
8	GLM-4v-Plus- 20250111		
9	0vis2-34B	34.9	Qwen2.5-32B
10	HunYuan- Standard-Vision		
11	Qwen2.5-VL-72B	73.4	Qwen2.5-72B
12	TeleMM		
13	GPT-4.1- 20250414		
14	ChatGPT-4o- latest		
15	GPT-4.5		





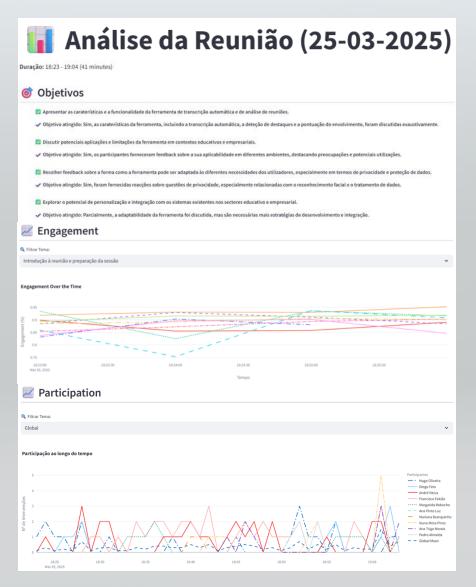
Platform

NEXI Platform

https://nexi-website.streamlit.app/

To enter the app on a guest mode, use the following credentials:

- Username: guest
- Password: GuestView_1







Thank you for your time.

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