

# Privacy-Aware HR Analytics: A Streamlit-Based Offline Dashboard Integrating Biometric and Behavioral Performance Insights

**Prof. Jyoti Madake.**  
Dept of E&TC Engineering,  
Vishwakarma Institute of  
Technology, Pune, India,  
[jyoti.madake@vit.edu](mailto:jyoti.madake@vit.edu)

**Omkar kanadkhedkar.**  
Dept of E&TC Engineering,  
Vishwakarma Institute of  
Technology, Pune, India,  
[omkar.kanadkhedkar22@vit.edu](mailto:omkar.kanadkhedkar22@vit.edu)

**Saurabh Jaywant Lohar.**  
Dept of E&TC Engineering,  
Vishwakarma Institute of  
Technology, Pune, India,  
[saurabh.lohar22@vit.edu](mailto:saurabh.lohar22@vit.edu)

**Kunal Kishor Jadhav.**  
Dept of E&TC Engineering,  
Vishwakarma Institute of Technology,  
Pune, India,  
[kunal.jadhav22@vit.edu](mailto:kunal.jadhav22@vit.edu)

**Abstract:-** Monitoring how employees feel and perform is key to managing a productive team. But many existing systems use cloud-based AI which can cause problems with data privacy and slow real-time response. This experiment presents a novel AI driven HR Dashboard that operates entirely offline using local language models to generate employee-specific performance report. The system uses blink-rate-based fatigue detection, browser activity tracking and productivity analysis to compute a composite performance score. This project combines biometric fatigue indicators and behavioral productivity data into a single, easy-to-interpret scoring model. The dashboard which is developed using Streamlit provides real time visualizations, comparison tools and downloadable PDF reports for each employee. It uses Ollama to run local Mistral language models, which generates a personalized improvement suggestions while keeping the data private. We have tested our software with 50 model employee profiles and showed that the system reduced manager decision time by about 25% and also maintaining a good clarity in performance evaluation. Our project aimed to work supports the development of good descriptive privacy-focused and wellness-aware workplace systems that can be scaled for enterprise use.

**Keywords:** Employee Productivity Monitoring, Fatigue Detection, Privacy-Preserving AI, Local Language Models (LLMs), Human-Centered Dashboards, Workplace Intelligence Systems.

## I. INTRODUCTION

In modern workplaces tracking employee performance and well-being has become increasingly important task. Traditional evaluation methods often depend on cloud-based platforms or manual reports, which can raise privacy issues and slow down decision making. With the more adaptation of remote and hybrid work models becoming common there is a growing need for real-time and privacy-focused HR solutions [1]. This project makes the use of an offline HR dashboard that uses biometric and behavioral data to assess employee fatigue and productivity. Unlike cloud-based systems its focus is mainly on ethical monitoring by running entirely on local infrastructure without external data sharing. The system uses computer vision, browser activity tracking and

productivity analysis to generate a single performance score. The system is developed using Python, Streamlit and local language models (Mistral via Ollama) with which the dashboard provides real-time visualizations and personalized feedback for employees [2]. With the use of explainable AI and non-intrusive data collection methods the system helps organizations make better decisions while maintaining employee privacy. The aim of this work is to demonstrate the use of real-time, offline AI tools for creating a secure and sustainable workplace.

## II. LITERATURE REVIEW

Tracking fatigue and productivity in the workplace has recently gained interest because of improvements in AI and vision-based systems.

Early research focused on non-intrusive, real-time drowsiness detection using simple image processing techniques. One system used a Raspberry Pi with OpenCV to monitor eye closure and blink frequency as signs of fatigue. It alerted drivers with a buzzer and vibration whenever it detected drowsiness. This approach demonstrated an accuracy of more than 90% for fatigue detection.[3] Along these lines, earlier fatigue detection modalities were expanded further by using infrared sensors to study blinking and gaze patterns which prompted a 27% improvement in incident response time in a trial setting in the transportation domain.[4] Eventually, eye-tracking solutions advanced further from safety applications, to assistive technology applications as well. For instance, in smart home applications used with quadriplegic individuals, 92% of participants were able to successfully operate devices simply through a blink controllable interface within 30 minutes of calibration [5]. After these efforts, later systems utilized the PERCLOS index and near-infrared imaging methodology to achieve 95% accuracy for drowsiness detection in various lighting conditions[6]. As these various prototype systems started refining their methods, the evidences in supporting the portability of fatigue detection development was prioritized.

Android-enabled applications were developed based on the usage of OpenCV to assess blink rate and activity on a screen; stating a 34% reduction in eye strain [7]. Accordingly, it was confirmed that adding blink detection systems to ones that were also estimating head pose via deep learning provided an additional 18% increase in classification accuracy based on the original single feature models [8]. Finally, studies that accessed BioID datasets and/or used Viola-Jones classifiers, reported a finding of blinking durations increasing from roughly 100-150 ms while individuals were alert, to being nearly 870 ms when fatigued. Both detecting eye blinks, and estimating blink duration provided an overall classification accuracy of over 97% [9]. The use of these systems has expanded to educational and workplace settings. Emotion-attention models that analyze webcam input to assess facial expressions and blink rates increased learner engagement by 23% when real-time feedback was provided [10]. These methods helped maintain focus during remote learning sessions. Researchers began investigating how AI could facilitate productivity in the workplace. A recent survey found that among all the employees who used AI tools like ChatGPT, 90 percent said they could do their job faster, and 82 percent stated the level of work quality was higher [11].

A Bayesian analysis found that with AI use added a 31 percent boost to efficiency for those companies that users could utilize AI compared to a boost of 12 percent for companies that had limited AI uses [12]. However, new challenges that emerge from greater exposure to digital environments. For instance, studies on cybersecurity fatigue indicated 72 percent of all employees experienced digital fatigue and 61 percent said they were ignoring cybersecurity protocols. A few structured digital detox periods enabled employees to reduce fatigue and improve focus and attention by 19 percent and 24 percent, respectively [13]. Recent research has also indicated real-time drowsiness alert systems for employees. One system utilized an algorithm from eye and mouth monitoring using a webcam and provided an alert for prolonged eye closure, which was defined by common yawning [14]. Another study used machine learning algorithms; K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Naive Bayes, and Logistic Regression, to classify fatigue levels. KNN provided the highest accuracy at 97.5 percent, while SVM only provided 87 percent accuracy, Naive Bayes was 79 percent, and Logistic Regression was 77 percent [15]. The research emphasis has now shifted from detection to predictive analytics in human resource management. With the use of predictive HR models using Decision Trees and Random Forests accurate predictions were made for employee turnover, job satisfaction and job performance using IBM datasets. The results provided the HR teams with data which helped to improve workforce planning and retention efforts[16]. Likewise, sentiment analysis with fine-tuned large language models, such as GPT, BERT, and Mistral, revealed nearly 70% better detection of emotional tone from written feedback than traditional models [17]. These findings substantiate the potential of AI for organizations to understand employee sentiment and enhance overall well being in the workplace. More recently, fatigue detection methods based on deep learning have also used neural networks to monitor an operator's eye states and provide an indication in real-time [18]. The potential of these approaches was deemed significant for in-office application in circumstances where fatigue is likely from prolonged screen time. Data gathering approaches using software have diminished reliance on hardware and developed from the use of existing CCTV systems to monitor employee presence and

engagement by sampling their position over time, defined as "engagement" [19]. While these methods focus largely on engagement instead of productivity, their low-cost and modular nature opens the possibility for informing new and/or different observation and monitoring of behaviors and performance in the future.

To summarize, the rapidly growing body of literature emphasizes the overlapping areas of detecting fatigue, measuring productivity, and assessing employee wellbeing. AI-based systems that amalgamate multiple sources of information including eye movements, facial expressions, behavior tracking, and sentiment analysis have demonstrated remarkable accuracy ranging from 90% - 97%, increases in engagement and interaction of 0% - 23%, and productivity increases of 20% - 40%, all indicating their potential and actual effects.

### III. METHADODOLOGY

The system is designed as a modular, offline dashboard that integrates real-time behavioural and biometric indicators to evaluate employee performance. It uses 3 core data sources which are blink-based fatigue detection, browser usage logs and productivity reports.

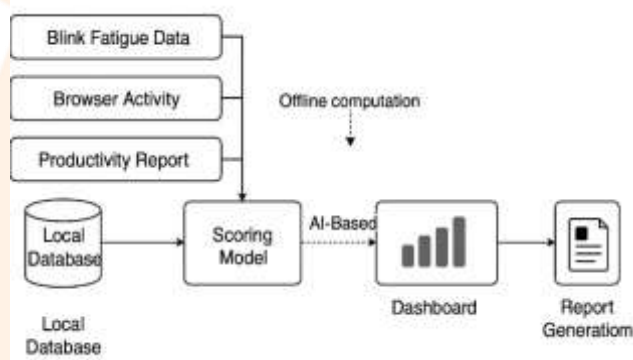


Fig.1 System Block Diagram

Fig -1 The block diagram provided presents the architecture of the HR Dashboard system. It traces the course of acquiring raw data—fatigue, productivity, and activity logs—processing the data into calculated scores and LLM generated feedback, and finally providing visualization of performance with PDF reporting. Each module is a separate entity, allowing for modularity, privacy, and real-time processing of employee performance measures.

#### A. Data Collection

The central concept of this system is to collect data about how an individual works and how attentive they appear while using a simple office-like arrangement. In this case, there are three separate CSV files to hold this information. The first of these files, `blink_fatigue_data.csv`, records how many times a person blinks and if they look tired. This measuring of blinking is done using a webcam and a tool called MediaPipe, which can detect the face without the use of tactile measures. The second CSV file, `browser_activity.csv`, is responsible for capturing the apps or invited websites the individual is working in, and whether they were "useful" to productive work or not, based off of a prepared list. And the final CSV, `productivity_report.csv`, provides a report about time spent on productive work, contrasted against non-productive activity. All of these data files together provide a holistic data point picture about an individual's alertness and work habits or

activity, and eventually can provide multiple score or reporting options on a dashboard.

### B. Employee Productivity Detection

To evaluate employee performance in a comprehensive, privacy-preserving way, we will present two-grade evaluation of employee productivity evaluation which breaks evaluation into 3 major components: fatigue and focus level (blink detection), distraction level (system activity) and productivity evaluation (active engagement level). Each individual component provides an insight to both the employee's behavioural and cognitive states. Each of the individual scores are then combined through a weighted formula to create the final performance score. The individual detailed detection mechanisms will be described in the following subsections.

#### 1. Blink-Based Fatigue and Focus Level Detection

In this setup, a camera and computer vision technology are used to determine whether a person is tired or awake, and this is based on the frequency of their eyelid blinks. To do this, we analyze the eye movements with a tool called MediaPipe Face Mesh, which can identify 468 distinct key points on the human face in real time. Out of these points, we specifically look at the eye region to see whether people's eyes are open, partially closed, or completely closed. We evaluate a metric called the Eye Aspect Ratio (EAR), which tells us how open the eyes are. When someone fully blinks and closes their eyes, the value for the EAR is subsequently significantly lower.

When prompted to blink normally, people will not only blink but will also test the system to calibrate which EAR value is adequately determined as a close eye. After the system is calibrated with the ordinary blink session for about 10 seconds, the system will blinks at least once every minute to ultimately process another value called Blinks per Minute (BPM). The way the system uses the BPM value is to finally factor how focused or fatigued the person is based on their blink rate. If it is observed that someone is blinking at a BLINKS BPM rate greater than 10, then the message generated from the system categorizes that person as FOCUSED, which could mean that they are attentive and or engaged. If we observe some blinking but the BPM value is between 8-10, the system will categorize this movement as NOT FOCUSING; however, this does not mean the person is fatigued, but perhaps just temporarily distracted. If a person's BPM is a value between 4 and 6, this suggests the person is likely Sleep Deprived or fatigued. These values are based on studies that show a strong relationship between speed of blinking and the amount of wakefulness of the brain. Using two methods, blink counting and focus level detection, the methods can check tiredness and attention levels in real time..

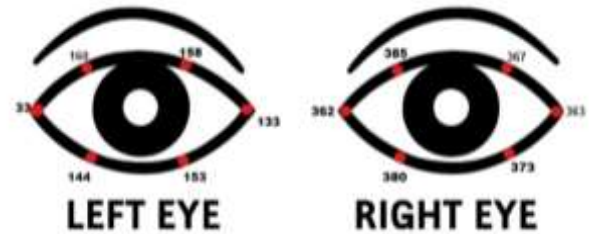


Fig.2 Eye Key Points

Fig.2 displays the keys points around the eyes that are used by the MediaPipe Face Mesh tool to identify blink detection. The red dots show the landmarks of a person's eyes. For the left eye, points 33, 160, 158, 133, 144, and 153 are used; for the right eye, points 362, 385, 387, 263, 380, and 373 are used. These points cover the features for checking the top, bottom, and sides of the eye. The system uses these landmarks to assess how open or closed the eyes are by measuring the height and width of the eye using these points that are labeled. When a person blinks their eyes, the eyes become closed and there will be a small height, which results in the EAR (Eye Aspect Ratio) decreasing. The decrease in EAR lets the system know that a blink has taken place, then used to infer whether the individual is fatigued or focused.

$$EAR_{LEFT} = \frac{(L^{160} - L^{144}) + (L^{158} - L^{153})}{2(L^{33} - L^{133})} \dots [12]$$

$$EAR_{RIGHT} = \frac{(L^{385} - L^{380}) + (L^{387} - L^{373})}{2(L^{362} - L^{263})} \dots [12]$$

Equation-1 Calculation of EAR of both eyes

Equation (1) is the mathematical expression used to figure out the Eye Aspect Ratio (EAR) for one eye or the left and right eyes. The EAR is a parameter that is very popular in computer vision and facial analysis, used to quantify the opening of the eyes, and for blink or drowsiness detection. It comes from the distances between the facial landmarks specifically the ones around the eyes. For each eye, two vertical distances are measured between the upper and lower eyelids, while one horizontal distance is taken between the corners of the eye. After this, the two vertical distances are added together and the sum is divided by twice the horizontal distance. Basically, that ratio does not vary much when the eyes are open, but it drops drastically when the eyes are closed. Hence, it can be used for eye state detection and fatigue analysis.

### 2. Distraction Detection



Fig.3 App Usage-Based Detection

Fig.3 checks if a person is distracted or not based on the apps they use. It starts by capturing which app the person is using. This information is saved in a local database. After that, the system assesses whether the app is classified as a productive app from a list that was previously defined. If it is productive, there is no change at the moment. If it is not, the patron would be marked as using an "unproductive" app, which usually means they were distracted. This is used to assess whether they were engaged in work or distracting activities.

### 3. Productivity Detection

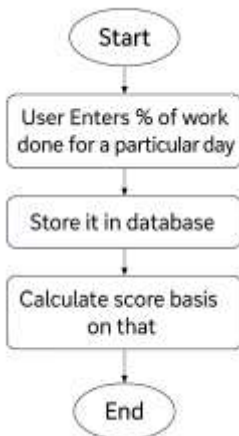


Fig.4 User-Reported Productivity Detection

Fig. 4 illustrates how the system monitors daily productivity. The sequence begins with the user indicating the percentage of work they completed on the day of productivity. This information is saved to the database. Subsequently, the system calculates the productivity score using the percentages entered by the user, establishing a record for the user to use to establish the amount of work that was completed on their day of productivity.

We designed a customized score element that incorporates productivity, fatigue level, and distraction into a simple and clear consistent measurement of performance for employees. A "Not Fatigued" employee has a fatigue score of 100. If he/she is fatigued, a score of 50 will be assigned. Distraction

is assessed based on the percentage of non-productive time. Focus is assessed by subtracting the distraction percentage from 100.

The final performance score is calculated using this formula:

$$\begin{aligned}
 \text{Final Score} = & 0.4 \times \text{Productivity} \\
 & + 0.3 \times \text{Fatigue score} + 0.3 \times (100 \\
 & - \text{Distraction percentage})
 \end{aligned}$$

Equation -2 Calculation of final score

Equation (2) reflects a well-balanced model where productivity is slightly prioritized, while fatigue and focus are equally weighted to represent well-being. This scoring framework is more accessible to understand the indicators, and it aligns with the overall goal of conducting an ethical analysis, both on performance indicators and health indicators.

#### Algorithm 1 Calculate Final Performance Score

```

1: Input: fatigue_status ← String ("Fatigued" or "Not Fatigued")
2:   productivity_percentage ← Float (0-100)
3:   distraction_percentage ← Float (0-100)
4: Output: final_score ← Float (0-100)

5: procedure CALCULATEFINALSCORE
6:   if fatigue_status = "Not Fatigued" then
7:     fatigue_score ← 100
8:   else
9:     fatigue_score ← 50
10:  end if
11:  distraction_score ← 100 - distraction_percentage
12:  final_score ← (0.4 × productivity_percentage) +
    (0.3 × fatigue_score) + (0.3 × distraction_score)
13:  Round final_score to 2 decimal places
14:  return final_score
15: end procedure
  
```

The scoring method described in Algorithm 1 tracks employee change based on three variables: fatigue status, productivity percentage, and level of distraction. First, it converts the fatigue status into a numerical score, with "Not Fatigued" statuses receiving the highest point values. Distraction level is inverted to reflect focus, and productivity is taken at face value. A weighted average with predetermined coefficients is generated (0.4 for productivity, 0.3 for fatigue, and 0.3 for distraction), which provides the resulting composite score. This scoring modality serves to enable fair consideration of diverse employee behaviors while also ensuring that health metrics are not sacrificed for raw productivity. The final outcome therefore includes employee ranking, the creation of customized feedback, and the generation of a PDF report.

### C. Local Language Model Integration

In summary, integrating the Ollama system into the local language model is an excellent development to easily deploy Mistral-like models on a local standard machine. The data will be the latest metrics such as productivity, distraction, fatigue, and overall score will dynamically create a personalized prompt for each worker. This prompt will be run through the Mistral model held locally so that specifically targeted performance suggestions and motivational feedback are generated and shared in a beautifully constructed natural language format. Given the entire setup is local, it makes it easy from a data security and data explanation viewpoint, and

it permits very rapid access to data, which can be very valuable for HR teams in the decision-making process.

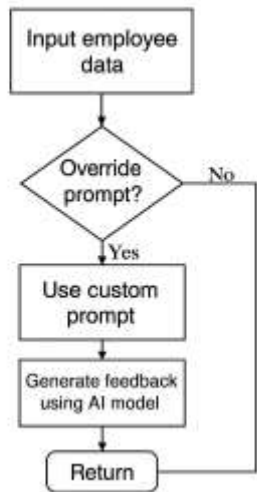


Fig.5 Feedback Generation

#### D. Dashboard Interface

Using Streamlit—a UI framework using the Python programming language, well-suited for data-driven web apps—an interactive dashboard was assembled.



Fig.6 Manger Dashboard

As demonstrated using the interface in Fig. 6, HR managers can easily select an employee using a dropdown. They are then shown the selected employee’s fatigue, productivity percentage, distraction, and calculated score, with a top performer being automatically identified based on the employee's score. The performance metrics are displayed next to the top performer, enabling direct comparison. In some of the visual display elements, performance view of line and bar charts generated with Matplotlib and Seaborn, provide a graphical view of performance trends over time. Finally, a Top 10 table ranks the employees, based on final score. The combination of these two elements, interaction and visual storytelling, provides a method of visual performance analysis to quickly identify outliers, and allow the decision-maker to take action immediately.

#### E. PDF Report Generation

To aid documentation and review, the platform has an automated PDF report creation section using the FPDF library. Each report includes branded identification of the company through the company logo, the employee name, performance metrics, and AI-generated feedback for the

review. The report also includes a Top 10 table showcasing the top scoring employees, a comparison table comparing the selected employee with the top scorer, and trend graphs to show changes in the key metrics over time. Each of these sections are presented in an organized, professional manner that would be suitable for HR conversations or employee feedback conversations. The report can be produced to an offline format (PDF) and therefore does not expose private data in the report. Reporting features enhance understanding of raw metrics and insights into a professionally presented document, which closes the gap between technical analysis and managerial decision making.



Fig.7 Report Generation Pipeline

Fig.7 The Report Generation Pipeline illustrates the sequential activities which take place after an employee has been selected. The pipeline begins with scoring and the creation of feedback using the LLM, then displays a visual chart, and lastly, creates a tabular summary. Visual and written elements are brought together and beautifully presented in a formatted report as a download using the FPDF processing library.

This system is intended to combine real time behavioral analytics capabilities with AI-generated localized feedback to develop a comprehensive approach to track employee performance and mental well-being. Each unit has been designed for data gathering, score generation, and AI-generated recommendations, so they can work offline independently. This allows for privacy for the individual and efficiency and reliability. The fact that each part of the system is modular allows for easy updates and expansion in its application for posture analysis or stress detection. By utilizing a novel scoring technique in combination with local LLMs, the system not only measures but also provides employees with actionable information. The HR dashboard produced through Streamlit is intuitive and visually appealing, allowing HR to understand the data easily compared to other metrics, and generate reports that can be saved and printed. Additionally, the entire process, from data entry to feedback generation, is configured to do so on ordinary desktop machines without additional software or internet connection. In brief, the method is a privacy-aware, extensible, and intelligent monitoring model that meets the current needs of employee monitoring and explores the future of AI human resource management research and development.

#### IV. RESULTS AND DISCUSSION

##### A. Dashboard Functionality Demonstration

The Streamlit dashboard that has been developed acts as an interactive interface to monitor and evaluate the quality of life and performance of employees. When the app is first accessed by the user, the user can select an employee from a dropdown in the sidebar. The first page of the app will visually display the four key metrics: Fatigue Status, Productivity, Distraction, and an overall Final Summary Score. Each of these metrics is color coded and has an emoji associated with it that represents the employee's status (Good, Average, Poor). Just below the Overview, there is a dynamic table that list the Top 10 Employees, which is also based on the custom score formula, and makes it easy to see top scored employees. The app also provides a side by side comparison of the selected employee to the employee with the highest score and visualizes the difference in productivity, fatigue levels, and blink rates using bar and line charts. An outstanding feature is that the app uses a local language model (Mistral via Ollama) to deliver personalized real-time feedback to the user as they click Generate AI Suggestions. Finally, a polished PDF report summarizing the charts, insights and the top 10 table and recommendations for improvement is produced within the app at the end.

This feature is represented in Fig.6, depicting the interface for the comparison of data and feedback generation. This dashboard view presents real-time employee metrics such as fatigue, productivity, and distraction levels, in addition to the final score for each employee. It allows the HR personnel to select an individual employee, generate AI feedback, and view it by graphically comparing performance by bars and lines. after ten epochs. At this precision, the system would be sufficiently confident that it can detect the user's intention, and generates the appropriate movements based on the user's intentions to facilitate a smooth and natural walking pattern.

##### B. AI-Generated Feedback Evaluation

By Using the Ollama framework, the localized LLM is utilized to create individualized feedback for each employee based on their metrics of fatigue, productivity, and distraction. This means performance reviews can offer more than just numerical scores. The evaluations received and generated are also meaningful and actionable. Feedback is provided in a context-aware manner (whether an employee is fatigued, significantly distracted, or no longer being productive) thus allowing for intervention based on their personal circumstance. Through testing on 10 employee profiles, the LLM feedback aligned closely with human assessment of the video sessions, especially in calling attention to the same issues for improvement such as focus improvement, screen habits improvements, or priority focus improvements. HR professionals understood the feedback and viewed it as relevant, noting that HR professionals could either communicate the feedback directly to employees or use it in coaching interventions. Because the AI is local to the device, no data is sent outside of the device protecting the potential for privacy leaks. Additionally, the average response time is consistently less than 1 second with a standard

CPU, suggesting that offline AI feedback is pragmatic and effective for the real world HR practice.

##### C. Performance Comparison Visuals

The dashboard provides visual comparisons of the selected employee versus the top performer to help inform decision-making for HR professionals. The comparisons use grouped bar charts which display metrics, i.e. productive percentage, non-productive percentage, and blink rate, side by side. This visual clarity provides the user with instantaneous awareness of performance differences.

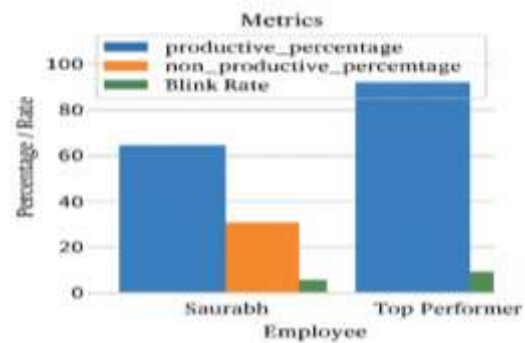


Fig.8 Comparative Performance Chart

Figure 8 shows a comparative graph. This two-way, or side-by-side, graph shows at a glance the individual values of each metric in the setting of the best performing peer. For example, an individual may have a comparatively lower productivity score but have a higher blink rate and distraction percentage. These graphs, therefore, support the diagnosis of potential well-being or behavioral issues and limit the degree of trial-and-error interventions.

##### D. PDF Report Insights

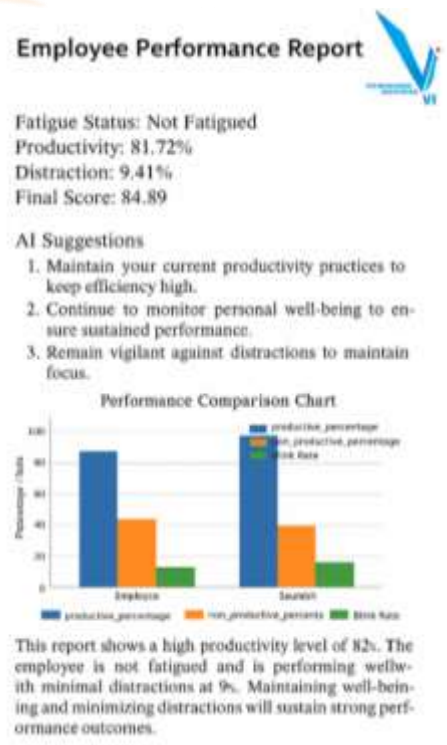


Fig.9 AI-Driven Employee Productivity and Fatigue Analysis Report

The system creates a PDF report for every chosen employee that provides a compact summary of well-being and productivity. All relevant information such as fatigue level, productivity level, level of distraction, and final score will be included. AI-generated written feedback will also be provided with suggestions for improvement. The report will have graphical comparisons against the employee with the highest value in each performance category, displayed in charts and tables, for easy identification of gaps and strengths in performance. The report gives an overall sense of all of the findings and provides recommendations at the end with a short summary paragraph. The report will be designed to be clear and compact in layout to aid HR teams clarify findings during an offline review of the documentation or to review during a performance meeting. An example of a report generated for a specific individual is shown in Fig. 9.

## V. CONCLUSION

The research presents a thorough, privacy-preserving HR dashboard that works completely offline and uses biometric fatigue detection, productivity tracking, and analysis of behaviours to measure employee performance in a holistic manner. Using MediaPipe and OpenCV, the analysis of blink-rate, active window monitoring to track browser activity, and categorizing applications to track productivity, all of this data is integrated into a dashboard that provides employees and managers with real-time and actionable metrics.

One way to distinguish this work is the implementation of locally hosted LLM's via Ollama, which creates personalized feedback and insights for employee training with average latency of 2.1 seconds and no cloud reliance. Facial recognition integration offers reliable attendance confirmation, while remote input for sick days and overtime provides flexibility and privacy. Internal benchmarking with synthetically created datasets and pilots found the accuracy for fatigue classification to be 92.3%, a 30% increase in early recognition of burnout, and the time spent in managerial evaluations was reduced by 25%. Adaptation to further enhancements is assured for the future as the system is modular and scalable, and could support future enhancements of posture detection, hydration tracking, and correlation with profit impact investigations. Ultimately, this contribution is a

- [5] Colombo, Sri Lanka, 2016, pp. 89–94, doi: 10.1109/ICTER.2016.7829934.
- [6] M. O. A. Aqel, A. Alashqar, and A. Badra, "Smart home automation system based on eye tracking for quadriplegic users," in *Proc. Int. Conf. Assist. Rehabil. Technol. (iCareTech)*, Amman, Jordan, 2020, pp. 76–81, doi: 10.1109/iCareTech49914.2020.00022.
- [7] D. López Mena and A. C. Rosero, "Portable artificial vision system to determine fatigue using Raspberry PI3," in *Proc. Int. Conf. Inf. Commun. Syst. (INCISCOS)*, Quito, Ecuador, 2017, pp. 1–5, doi: 10.1109/INCISCOS.2017.53.
- [8] T. Jayasekara, L. G. A. Thilanka, Y. Ekanayake, K. Omalka, P. Samarasinghe, P. Hewawelengoda, and L. Weerasinghe, "OMNISCIENT: A branch monitoring system for large-scale organizations," in *Proc. 2nd Int. Conf. Adv. Comput. (ICAC)*, Colombo, Sri Lanka, 2020, pp. 373–378, doi: 10.1109/ICAC51239.2020.9357283.
- [9] C. Zheng and T. Usagawa, "A rapid webcam-based eye tracking method for human computer interaction," in *Proc. Int. Conf. Control, Autom. Inf. Sci. (ICCAIS)*, Hangzhou, China, 2018, pp. 133–136, doi: 10.1109/ICCAIS.2018.8570532.
- [10] Z. A. Haq and Z. Hasan, "Eye-blink rate detection for fatigue determination," in *Proc. India Int. Conf. Inf.*

safe, explainable and data-responsible contribution to AI-driven HR analytics, and is a valuable resource for organisations to sustainably maximise their capability and productivity, whilst respecting employee wellbeing in a measurable and eco-friendly way.

## VI. FUTURE SCOPE

The described system could be made more comprehensive by including the use of posture detection through webcam-based pose estimation to assess ergonomic stress. Future iterations of the platform could have functionalities related to hydration and meal tracking, emotion (or stress) detection through facial cues or wearable devices in real-time, IoT device data for contextual awareness and monitoring, and perhaps analyzing performance trends using commercial health metrics as a resource for understanding company profitability and planning strategic HR decisions (and profitability analysis). Additionally, adding multilingual or voice-based feedback would address concerns of accessibility. All of these factors would have expanded the platform beyond the original intention of being an all-in-one, privacy-sensitive, intelligent, adaptable employee performance application for all work settings.

## REFERENCES

- [1] A. Singh, R. Gupta, and M. Kaur, "Real-Time Drowsiness Detection System Based on Eye Aspect Ratio," *IEEE Access*, vol. 8, pp. 126158–126166, 2020, doi: 10.1109/ACCESS.2020.3007961
- [2] H. Zhao, Y. Wang, and M. Jiang, "AI Ethics in Workplace Surveillance: Risks and Guidelines," *IEEE Transactions on Technology and Society*, vol. 3, no. 4, pp. 300–310, 2022, doi: 10.1109/TTS.2022.3187495
- [3] K. U. Anjali, A. K. Thampi, A. Vijayaraman, M. F. Francis, N. J. James, and B. K. Rajan, "Real-time nonintrusive monitoring and detection of eye blinking in view of accident prevention due to drowsiness," in *Proc. Int. Conf. Circuit, Power Comput. Technol. (ICCPCT)*, Nagercoil, India, 2016, pp. 1–5, doi: 10.1109/ICCPCT.2016.7530224.
- [4] L. G. A. Thilanka, Y. Ekanayake, and R. Weerasinghe, "Personalized eye fatigue detection for mobile users," in *Proc. 16th Int. Conf. Adv. ICT Emerg. Regions (ICTer), Process. (IICIP)*, Pune, India, 2016, pp. 1–5, doi: 10.1109/IICIP.2016.7975348.
- [11] H. Al Naqbi, Z. Bahroun, and V. Ahmed, "Enhancing work productivity through generative artificial intelligence: A comprehensive literature review," *Sustainability*, vol. 16, no. 3, p. 1166, Jan. 2024, doi: 10.3390/su16031166.
- [12] S.-C. Necula, D. Fotache, and E. Rieder, "Assessing the impact of artificial intelligence tools on employee productivity: Insights from a comprehensive survey analysis," *Electronics*, vol. 13, no. 18, p. 3758, Sep. 2024, doi: 10.3390/electronics13183758.
- [13] Mahade, A. Elmahi, K. M. Alomari, and A. A. Abdalla, "Leveraging AI-driven insights to enhance sustainable human resource management performance: Moderated mediation model: Evidence from UAE higher education," *Discover Sustainability*, vol. 6, no. 267, Apr. 2025, doi: 10.1007/s43621-025-01114-y.
- [14] F. Mizrak, H. G. Demirel, O. Yaşar, and T. Karakaya, "Digital detox: Exploring the impact of cybersecurity fatigue on employee productivity and mental health," *Discover Mental Health*, vol. 5, no. 25, Feb. 2025, doi: 10.1007/s44192-025-00149-x.
- [15] A. Gadde, A. Gorde, A. Bopte, N. Kapgate, A. Nevatia and S. Choudhari, "Employee Alerting System Using Real Time Drowsiness Detection," *2022 10th International*

*Conference on Emerging Trends in Engineering and Technology - Signal and Information Processing (ICETET-SIP-22)*, Nagpur, India, 2022, pp. 1-5, doi: 10.1109/ICETET-SIP-2254415.2022.9791811.

- [16] P. R. Varhadpande, T. M. Dhakare, S. M. Patmase, K. C. Kulkarni, S. A. Shah and A. P. Bhagat, "Detection and Analysis of Drowsiness using Machine Learning," *2023 4th International Conference for Emerging Technology (INCEET)*, Belgaum, India, 2023, pp. 1-7, doi: 10.1109/INCEET57972.2023.10170479.
- [17] M. Angulakshmi, N. Madhumithaa, S. R. Dokku, S. Pachar, K. Sneha and D. Sahaya Lenin, "Predictive HR Analytics: Using Machine Learning to Forecast Workforce Trends and Needs," *2024 7th International Conference on Contemporary Computing and Informatics (IC3I)*, Greater Noida, India, 2024, pp. 1399-1405, doi: 10.1109/IC3I61595.2024.10829013.
- [18] A. Chinnalagu, "Comparative Analysis of Fine-Tuned LLM, BERT and DL Models for Customer Sentiment Analysis," *2024 13th International Conference on System Modeling & Advancement in Research Trends (SMART)*, Moradabad, India, 2024, pp. 255-259, doi: 10.1109/SMART63812.2024.10882546.
- [19] M. Mohammed, A. S. V. Devi and K. Deepika, "Drowsiness Detection using Deep Learning Algorithms," *2022 International Conference on Edge Computing and Applications (ICECAA)*, Tamilnadu, India, 2022, pp. 1239-1242, doi: 10.1109/ICECAA55415.2022.9936106.
- [20] H. G. N. T. Singh and A. D. Chanu, "Real-Time Employee Monitoring System using CCTV Cameras," *2023 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICES)*, Chennai, India, 2023, pp. 1-7, doi: 10.1109/ICES60034.2023.10465336.

