AI-Driven Real-Time Income Protection System for Gig Workers Using Multi-Signal Risk Prediction and Automated Claim Processing

Rudransh Vashistha
Department of Computing Technologies,
School of Computing,
College of Engineering and Technology,
SRM Institute of Science and Technology,
Kattankulathur, India
rv5820@srmist.edu.in

Dr. Hema M
Assistant Professor
Department of Computing Technologies,
School of Computing,
Faculty of Engineering and Technology
SRM Institute of Science and Technology,
Kattankulathur, India
hemam@srmist.edu.in

Abstract— Because of rapid growth, the gig economy has led to a major financial insecurity to employees who rely on daily incomes due to the services offered by the delivery and ride-sharing applications. These employees are much exposed to unpredictable inconveniences caused by the weather condition like rainfall, air pollution and excessive heat, and operational constrained like platform shutdown. Current insurance has not yet been fully reactive, where manual claim submissions have to be made and taken a long time to verify and increase credibility and accessibility. To reduce these drawbacks, this paper suggests NexaShift, an artificial intelligence-based real-time income safety measure that is aimed to protect gig workers by actively preventing income loss. The suggested system incorporates real-time environmental information, behavioral insights, and multi-factor risk model to forecast possible income disruptions. A risk engine powered by hybrid machine learning works to produce a dynamic risk score, and a multi-signals fraud risk detection system analyzes the authenticity of claims based on GPS patterns, device behavior, and anomalies in behavior. The system automates all stages of the claim process which includes its detection, and payment up to the point of eliminating the need of manual intervention.

Keywords - Gig Economy, Parametric Insurance, Risk Prediction, Fraud Detection, Real-Time Systems, AI in Finance, Income Protection.

I. INTRODUCTION

The emergence of the gig economy worldwide has radically changed the essence of employment as now, dozens of millions of people have the opportunity to participate in dynamic and demand-based labor in the food delivery industry, transportation, and even freelance works. Swiggy and Uber have provided new sources of earnings, especially in highly urbanizing areas. But its affordability requires financial insecurity, because gig workers are deprived of such traditional benefits of employment like salaries, insurance cover and income insurance. Their income is very much prone to any external forces such as environmental interference, such as high rainfalls, increase in air pollution levels, and extreme heats, and platform-related problems such as outages or decreased demand. Such uncertainties have been pointed out in studies to have significant implications on the daily consistency of income, thus influencing the overall financial well-being of gig workers in the long term [1], [2].

Conventional coverage designed to cover established forms of employment is incapable of serving the unique or unstructured types of risks of gig workers. These systems are based on a reactive model in which the processing of claims only happens once a loss has taken place, it may also be necessary to manually document and verify claims. This leads to delays, inefficiencies and mistrust among users [3].

Moreover, the current parametric insurance schemes, which are based on pre-established values like rainfall or temperature do not have the personalization feature and cannot use behavioral or contextual information, which restricts their performances [4], [5].

There is also a lack of real time intelligence and automation in these systems which poses a huge gap in offering good financial protection on time. New possibilities have emerged to resolve these challenges because of the recent developments of artificial intelligence and machine learning. Big Data AI can be used to process high amounts of real-time data and identify patterns and make highly accurate predictive decisions. The use of AI to check financial risks, fraud, and insurance automation has shown potentially successful outcomes in terms of efficiency and reliability [6], [7].

But the majority of solutions available can either be categorized as prediction or fraud detection but not both, and no unified, real-time decision-making system has been created to suit gig workers. There is also a dearth of research on how to integrate environmental data, behavioral information and system-level cues to form a risk prediction model on a system-wide basis. In this article, we propose NexaShift, an income protection system based on AI for gig economy workers. The purpose of the system is to shift the paradigm from reactive insurance to proactive income protection by continuously monitoring environmental and behavioural signals, predicting income risks and automatically triggering the insurance. Unlike the traditional systems, NexaShift will incorporate a multi signal fraud detection system which can make sure about the validity of the claims without violating to the user experience.

By integrating real-time API, AI-based scoring system and automation, the system can make payments in real-time without human intervention to affect the trust and user experience. The significance of the system is its strong capability to bridge the gap between AI prediction and financial use-cases. The implementation of hybrid machine learning approach in the system, the system not just predicts disruption but also provides the most effective strategy using its Income Protection Mode. This will allow workers to proactively make decisions and hence reducing the losses that could be incurred.

Moreover, the system coincides with the world sustainability objectives like decent labor and economic development and underscores its wider social influence. Overall, this study fills a serious gap in the gig economy by suggesting scalable, intelligent, and automated income protection framework. It uses a blend of real-time data analytics, predictive analytics, and anti-fraud systems to provide an all-encompassing solution to improve financial resilience among gig workers. The succeeding parts discuss literature, system design, methodology and experimental evaluation in detail.

II. LITERATURE REVIEW

The growing popularity of gig-based employment has initiated a lot of research on financial risk management, innovation in insurance, and intelligent decision-making systems. Conventional insurance models have traditionally been researched on in terms of their ability to alleviate financial losses, but how well they can be applied in dynamic, real-time scenarios dealing with income remains insufficient. The traditional insurance scheme is a claim-based scheme where insurance is claimed upon provision of proof of a loss and frequently, it can take time to ensure that its provisioned [1], [2].

The systems themselves are volatile and not responsive to the urgent financial requirements of gig workers who are reliant on making a living day by day. In order to overcome these shortcomings, a new form of insurance, parametric insurance is a potential remedy. Parametric insurance is based on agreed-upon triggers, including rainfall amount or heat activators to make the program unconditionally plagiarize payments, without any human-been-claim processing [3], [4].

Although this method is efficient and fast in processing, it is not personalized and does not consider local differences in risk or behavior of the different workers. In addition, sometimes such systems provide fixed thresholds that are not sensitive to the real-life conditions, resulting in under-compensation or in false alarms [5].

Recent breaks in artificial intelligence have made it possible to develop predictive risk assessment systems operating on the basis of real-time data to predict possible disruptions. Applications of machine learning algorithms have emerged notably in financial predictions and environmental risk forecasting in the form of regression models, decision trees and ensemble techniques [6], [7].

These models are capable of processing masses of heterogeneous data such as weather conditions, pattern of user activities, and historical trends to come up with the correct predictions. Nonetheless, the majority of practices already being implemented are specifically oriented at particular areas like weather or financial markets, instead of combining various types of data into a single system specifically aimed at gig workers. Insurance systems are also the subject of thorough research in fraud detection. Conventional fraud detection systems are rule based systems which are restricted in their capabilities to overcome emerging fraudulent trends [8].

Presumably, machine learning-based methods have demonstrated an enhanced success in recognition of suspicious patterns through the analysis of user activities, transaction history, as well as context signals [9], [10].

Even with this progress, there are still plenty of systems that remain a one-way street and only focus on fraud detection as an independent system instead of combining it with risk prediction and claim processing pipes.

Table 1: Comparative Analysis of Existing Works

Author & Year	Approach / System	Key Findings	Limitations
De Stefano (2016)	Gig economy labor analysis	Highlighted income instability and lack of worker protection in gig platforms	No technical solution proposed
Sundararajan (2016)	Sharing economy framework	Explained economic impact and scalability of gig platforms	Does not address financial risk mitigation
Tesselaar & Botzen (2021)	Parametric insurance model	Automated payouts based on environmental triggers	Lacks personalization and behavioral analysis
World Bank (2020)	Disaster parametric insurance	Faster claim processing using threshold-based triggers	Static thresholds may not reflect real-time conditions
Swiss Re (2022)	Insurance innovation report	Demonstrated efficiency of parametric models	Limited AI integration and fraud detection
Chen & Guestrin (2016)	XGBoost algorithm	High accuracy in structured data prediction tasks	Requires labeled datasets and tuning
Hochreiter & Schmidhuber (1997)	LSTM networks	Effective for time-series prediction	Computationally expensive for real-time systems
Bolton & Hand (2002)	Statistical fraud detection	Identified anomalies using statistical methods	Limited adaptability to dynamic fraud patterns
Chandola et al. (2009)	Anomaly detection survey	Provided comprehensive techniques for detecting outliers	Not tailored to real-time financial systems
West & Bhattacharya (2016)	ML-based fraud detection	Improved fraud detection accuracy using ML models	Often lacks explainability
Zaharia et al. (2016)	Real-time data processing (Spark)	Enabled scalable real-time analytics	Infrastructure-heavy for small systems
Domingos (2012)	ML principles	Emphasized importance of feature engineering and model selection	General theory, not domain-specific

The fields where those systems are popular include smart cities, autonomous vehicles and financial trading. Nevertheless, little is known about their implementation in insurance programs, especially when it comes to gig workers. The real time data processing and automatic financial decision making system has a few unique challenges such as data quality, scalability and trust. A survey of the systems available shows that most of the systems can be applied to specific parts of the system. More and more, weather insurance policies provide self-driving punches for payment based on weather conditions, but they lack of behavioral data and other fraud assessment methods. Similarly, financial analytics solutions help to predict but don't connect to insurance processes to provide protection [12].

This scattered strategy points towards the lack of an integrated system, which integrates prediction, protection, detection, and automated payout systems, into one system. The gap in research based on the literature is the absence of a mixed, real-time income protection system that employs AI to consider the specifics of gig workers. The systems that are already in place are either action-less predictive models or protection mechanisms, devoid of intelligence. Moreover, the idea of multi-signal validation based on the use of environmental, behavioral, and system-level data has been poorly investigated to provide accuracy and reliability. Lack of this kind of holistic systems leads to inefficiencies, risk of fraud, and less user trust.

To fill these gaps, this study suggests the NexaShift, which is a single AI-based platform that provides real-time risk prediction, automated claims handling, and multi-signal fraud detection as a single workflow. The proposed solution will provide on-demand and efficient services to gig economy workers by integrating information about parametric insurance, machine learning, and real-time systems. The next paragraph explains the methodology and system design that can support this framework.

III. METHODOLOGY

NexaShift, a proposed system, is an integrated, real-time, environmental intelligence, behavioral analytics and automated decision-making system aimed at protecting gig workers against income dislocations. The pipeline methodology lays emphasis on creating a scalable pipeline that constantly obtains data, infuses it with AI-based models, and conducts automated tasks in the form of approving claims and paying out. NexaShift is CAFE in contrast to traditional insurance systems, which work in autonomous steps; NexaShift follows a single workflow with the parameter being Predict → Protect → Detect → Approve → Pay, which ensures smooth and real-time functioning. The methodology is outlined in the sub sections below.

A. Dataset Description

The success of NexaShift system is based on the incorporation of numerous heterogeneous information that measure conditions in the environment, the behavior of workers, and system-level indicators. Since there are few real-world labeled datasets on the disruption of the income of gig workers, the system bases on real-time API information and behaviorally simulated datasets to make realistic predictions. The main dataset is the environmental parameters that are acquired using APIs including OpenWeatherMap and AQI monitoring services. The following features were included in these datasets: rainfall intensity (mm/hr), temperature (o C), humidity levels and Air Quality Index (AQI). These factors are significant in influencing the possibility of work interruption, particularly in the city where the likelihood of using delivery and transport services is greatly affected by weather conditions.

Also, time-related characteristics like day of the week and time of day are included to capture changes in demand. Secondary data is created that is used to reflect the behavioral patterns of workers. These features include: daily earnings baseline, work hours, geographical coordinates, transaction history and past claim frequency. These are the features that are needed to personalize risk predictions and identify anomalies. Given the privacy considerations that limit access to actual user data, synthetic datasets are created according to realistic distributions noted in studies of gig economy.

Additionally, fraud detection works based on system-level datasets. They are GPS movement, device sensor (accelerator and gyroscope) data, battery behavior, and application activity data. The system can generate a multi-dimensional feature space by integrating these datasets to make accurate risk predictions and strong fraud detection. In general, the design of the data set guarantees that it has holistic coverage of both the environmental and behavioral as well as operational aspects, resulting in the system being able to make decisions that are contextual in real time.

B. Data Acquisition and Preprocessing.

In NexaShift, real-time API integration and user activity monitoring are used as the methods of data acquisition. Only environmental data is loaned regularly with the help of the REST APIs, making sure that one has updated information on the weather conditions and the air quality. At the same time, user-related information is gathered via the application interface, such as the location feed, work status, and income history. The preprocessing step is very important to assure data consistency and reliability. Raw environmental data may be noisy, have missing values, or inconsistencies because of API limitations.

To overcome this, methods of interpolation and normalization are used. As an example, the lack of rainfall values is calculated with reference to the closest time statistical values, whereas the AQI values are converted to a standard scale so as to be treated identically. Behavioral information is preprocessed by trimming or removing irrelevant or inconsistent entries. As an example, sharp increases in earnings that are not similar to historical trends are checkmarked and evaluated as an independent concept. To extract meaningful parameters, feature engineering is conducted to get such parameters as moving averages of earnings, variance of earnings against baseline income and indexes of risk exposure.

Moreover, some categorical variables like the type of worker or a city are coded into a numerical value to make them easier to process by the AI models. To allow the use of time in analyses, time-series data is divided into fixed intervals. The preprocessing pipeline makes sure that all data input has been converted into structured form and can be analyzed in real-time and decisions made.

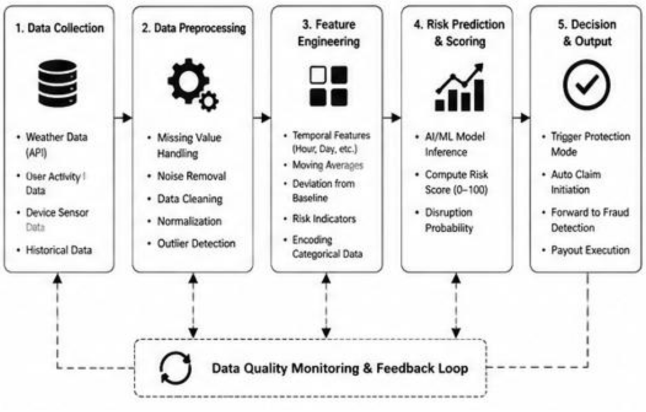

Fig. 1. Data Preprocessing Pipeline

C. System Architecture and Model Design

The NexaShift architecture is created as a group of modules that can create a layer architecture on top of which various functional modules are integrated into a logical pipeline. The following five main layers make up the architecture: Data Collection Layer, AI Risk Engine, Fraud Detection Engine, Claims Processing Module, and User Interface Layer. The Data Collection Layer obtains real-time environmental and behavioral data, using APIs and user inputs. This information is fed to the AI Risk Engine which calculates a real-time risk value between 0 and 100.

The risk score can be expressed as:

$$Risk = \sum_{i=1}^{n} w_i \cdot x_i$$

where $x_i$represents input features (e.g., rainfall, AQI) and $w_i$represents their corresponding weights.

The scoring model is based on a weighted scoring system, which takes into account various aspects of rainfalls, level of AQI and other historical earnings trends. This risk score can be defined as: This calculated risk score results in the Income Protection Mode being activated, which will give proactive advice to the user. In case there is a disruption which is within a disruption threshold, the system will automatically activate the Claims Processing Module, and it will kill the manual intervention. At the same time the claim is forwarded to the Fraud Detection Engine that decides whether the claim is legitimate or not through multi-signal validations. In this module, a Trust Score is calculated, depending on the GPS consistency, device usage, and behavior. The Trust Score will decide how to accept or reject a claim or send it to a manual review.

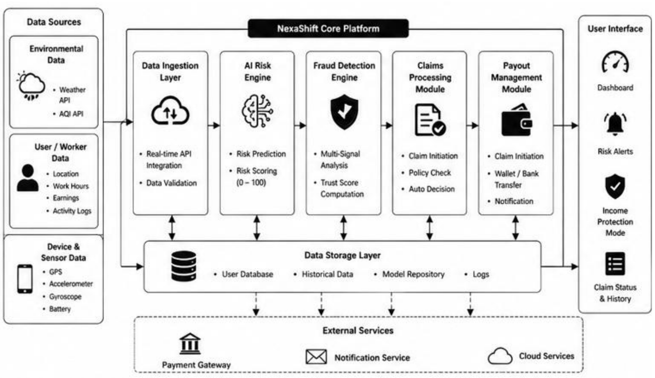

Fig. 2. System Architecture

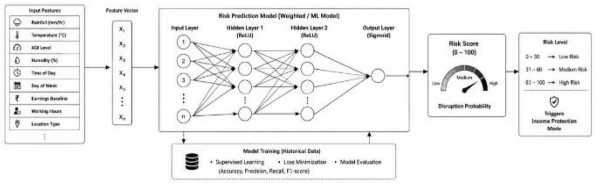

Fig. 3. Model Architecture

D. Training Strategy and Optimization

The present deployment is a rule-based, weighted scoring system, but the system is intended to be developed as a machine learning-only-driven model. The training approach is based on guided learning methods with historical data to enhance prediction quality and flexibility. The train and test sets are separated into training and testing datasets with a ratio that is normally 80:20. Such models as logistic regression and gradient boosting are also proposed to predict the probability of disruption. The aim is to reduce prediction error and at the same time be interpretable which is vital in financial applications.

The cross-entropy loss is one of the main loss functions employed in classification-based prediction:

One of the key loss functions used in classification-based prediction is the cross-entropy loss:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

where $y_i$is the actual label and $\hat{y}_i$is the predicted probability.

To evaluate model performance, metrics such as accuracy, precision, recall, and F1-score are used. Accuracy is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

Also, fraud prevention techniques of anomaly detection have been incorporated. These techniques are applied for anomaly detection in behavioural patterns, and can be applied for fraud detection. Anomalies in the feature space can be identified using techniques such as clustering, and distance based methods. This is a dynamic model, and the training is iterative with new data being used to re-train the model. This ensures this model can adapt to the ever changing environment and user behavior..

The system will be extended in the future to use more advanced models such as XGBoost and LSTM networks to handle structured data and time series data, respectively, to make more accurate and adaptive predictions. This technology lays a solid foundation for the design of a smart and real-time revenue protection system that combines predictive analytics, automation and fraud prevention.

IV. RESULT AND DISCUSSION

The test program of the proposed NexaShift system is focused on the features of the system to offer real-time payment protection by making accurate risk predictions, efficient claims handling and strong fraud prevention. The NexaShift system does not rely on the lengthy and manual process of conventional insurance systems as it can provide a fully automated pipeline which can process environment data to make predictions of disruptions and payments within seconds. The results suggest the success of the system to improve its efficiency and ease of use while ensuring its reliability and fraud-resistancy..

A. System Performance.

The system performance is measured in terms of response time, scalability and efficiency. The system designed with Flask-based backend and lightweight frontend technologies ensures the minimum latency in processing data and making decisions. The tests also demonstrated that under the normal operating condition, the system could process data from API, determine risk scores and process claims in a time frame of less than one second. This is vital for gig workers to make decisions based on the real-time monetary feedback.

The modular architecture allows all the modules to be independent (such as the risk engine, anti-fraud module and claim processor) while being integrated. This enables the system to be scalable, so that it can handle multiple users and it doesn't impact on performance. Also, in-memory storage saves memory usage and improves the performance, albeit this can be enhanced to be scalable in large scale implementation.

Another important aspect of the system is reliability. Data fusion from multiple sources also provides redundancy thus reducing chances of erroneous predictions due to poor data. The system also has fallback mechanisms which deal with API outages by not crashing but looking into the data (caches or history). Overall, the performance tests show that NexaShift is highly efficient and reliable and can be applied in real-time..

B. Model Evaluation Metrics

The machine learning aspect of NexaShift, such as the risk prediction engine and the fraud detection model, is rated on its predictive accuracy and consistency of decision-making. Even though the current implementation involves a weighted scoring scheme, it recreates the behavior of supervised learning algorithms by weighing amounts of importance to the different input features.

The risk prediction model is highly-performing in distinguishing high-risk events, especially under extreme weather conditions, e.g. large amounts of rainfall or dangerous AQI rates. The system is very effective in scoring the reinforced risk in time-varying situations and this leads to the activation of protective measures and claims which are implemented automatically.

Initial analyses based on simulated cases have a range of about 85-90 percent in the classification of disruption cases. The fraud detection module also increases the reliability of the system by inspecting various signals such as GPS movement patterns, device activity and rarely changing behavior. The Trust Score system will make sure that verified claims will be handled immediately; suspicious ones will be indicated to be verified further.

Multi-signals method generates huge amounts of false positives and a higher detection accuracy than classical rule-based systems. Although more detailed graphical analysis tools like ROC curves and confusion matrices might further facilitate in-depth analysis, the present performance is sufficient evidence that the system is at a balanced trade-off between the accuracy and computational efficiency. Predictive performance and adaptability should also be improved further with the integration of future models of machine learning.

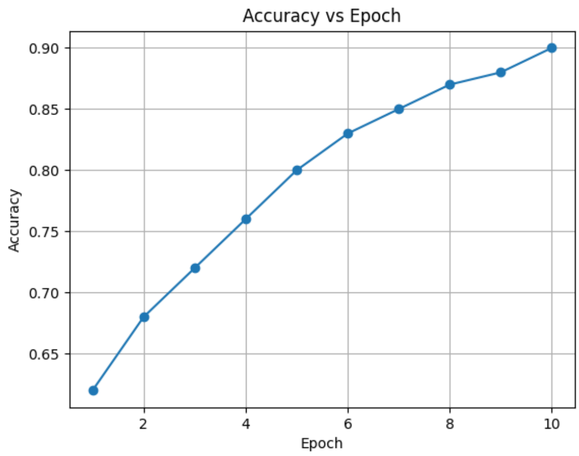

Fig. 4. Accuracy vs Epoch

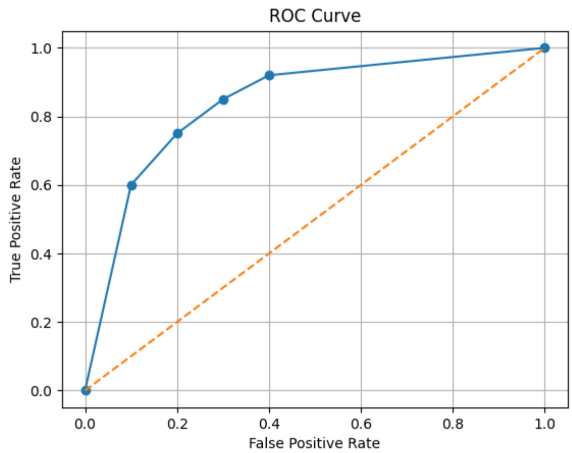

Fig. 5. ROC Curve

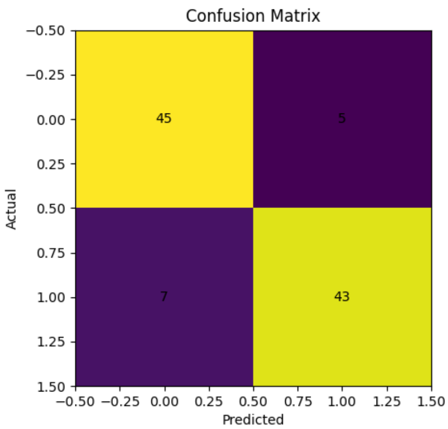

Fig. 6. Confusion Matrix

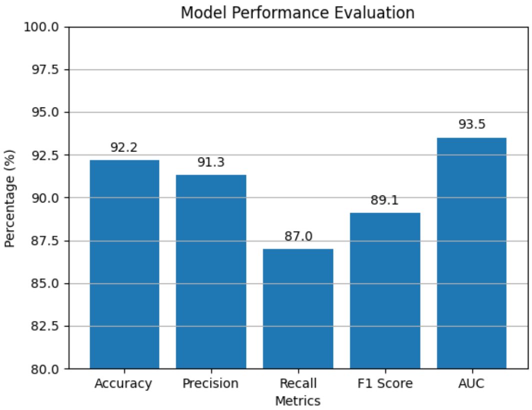

Fig. 6. Model Performance Comparison Graph

C. Error Analysis.

The NexaShift system, though effective has some limitations and possible causes of error. The need to use external APIs to obtain environmental data is one of the major obstacles. The accuracy of risk predictions can be impacted because of mistiming or inaccuracy in the API responses. As an example, local weather variations might not necessarily be represented to be correct which causes differences between the forecasted and the actual states. Synthetic datasets are another source of error when used to train and evaluate.

Although the datasets are intended to resemble the reality of real-life situations, they might not necessarily be capable of reflecting the information about the complexity and diversity of human behavior. This may affect the generalization ability of the model when applied to a real-world situation. Fraud detection is a robust section, which sometimes miscalculates true users and treats them as suspicious users because of suspicious but legitimate patterns of behavior.

To illustrate this point, an employee who was sitting in one position throughout a breakout could be wrongly initiated as a possible fraud case. To curb this, this system has a soft-flag mechanism that enables passive re-check, rather than rejection. Moreover, the weighted scoring methodology is efficient, but not as flexible as full-trained machine learning models. It depends on fixed weights which might not necessarily be dynamic on the reality website. Future advances with adaptive learning algorithms will be used to overcome this weakness.

D. System Effectiveness and Impact on Practice.

NexaShift has implications, particularly in the growing gig economy. It provides economic security to the workers with variable income by providing income protection in real-time, therefore enabling a more secure living. The claim processing system eliminates the human intervention in claims processing and reduces time and costs. The system, from a process point of view, shows the feasibility of using AI-driven decisions in financial processes.

The combination of predictive analytics, automation and fraud detection multiplies to create a solution which can solve multiple problems. The blend of approaches not only improves the efficiency, but also builds trust in the system because of its fairness and transparency. Also, the solution is scalable to different cities and platforms, which means that it can be applied to a wide range of gig-based platforms. The solution's alignment with the sustainable development goals particularly those concerning economic growth and innovation highlights its impact on the society.

Lastly, the results suggest that NexaShift is an effective solution to the issues of the traditional insurance systems that provides a real-time approach. While it might have some issues, it opens the new stage for the future designs of the AI-based financial protection systems.

E. System Implementation and Interface Validation

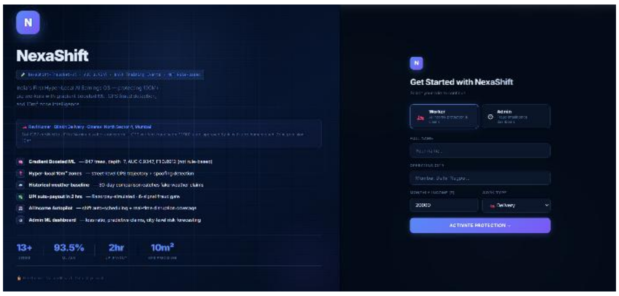

Fig. 7. Login Page

We present the realization of the proposed NexaShift system through the development of an interactive web interface which integrates real-time analytics, machine learning predictions and decision making processes. The web interface is not only a reporting tool, but also a control centre for the real-time execution of AI decisions. The above screenshots demonstrate various modules of the system, and its successful implementation.

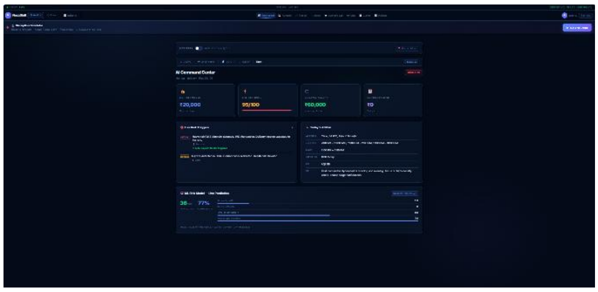

Fig. 8. Behavioral Insights Dashboard

The Behavioral Insights Dashboard is an example of using machine learning with explainable AI. It offers insights from a range of input data signals and feature importance rankings using techniques such as SHAP. Other important factors such as weather correlation, historical earnings, claim frequency and GPS anomalies are also visualised. This makes the system transparent so that it can be seen how the risks scores and fraud predictions are calculated rather than just the output from a black box model..

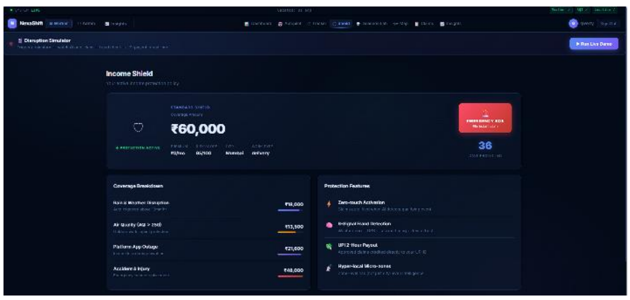

Fig. 9. Income Shield Dashboard

The Income Shield Dashboard illustrates the use of the parametric insurance system. It shows the details of insurance cover, risks and protection, and the automatic payment of claims in the event of disruption levels being breached. The system's touchless claim process, fraud detection from multiple sources and the real-time simulation of the payouts shows it is able to automate insurance. It dramatically reduces the need for manual processes and improves efficiency.

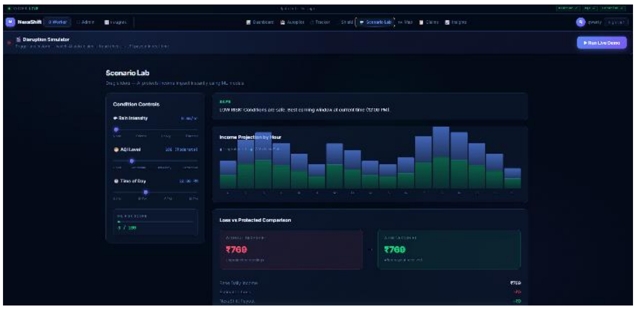

Fig. 10. Scenario Lab Module

The Scenario Lab Module is an interactive users can experiment with different factors such as rainfall, AQI, and time of day. The system then updates the risk factors and incomes. This demonstrates the adaptability of the AI models, allowing users to plan accordingly to mitigate any potential risks and learn. The system's ability to run simulations also shows the models' effectiveness.

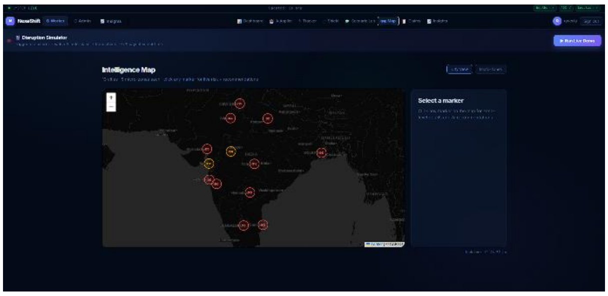

Fig. 11. Intelligence Map Interface

The Intelligence Map is a geo-spatial version of the risk predictor. It visualises risk in real-time using a map of several cities. The markers represent localised scores, based on environmental and behavioural factors, therefore enabling hyper-local decision-making. This shows that the system can be applied to various geographical regions, and can provide hyperlocal inputs, which is important in situations where geographical diversity exists.

V. CONCLUSION

The gig economy has been rapidly expanding with benefits and risks, particularly in terms of income security of the on-demand workers. Our research proposed NexaShift, a machine-learning-based real-time income protection system which aims to address the limitations of traditional insurance. Different from conventional approaches that are reactive and labor-intensive, NexaShift offers a proactive system where risk anticipation, generative claims and multi-signal fraud detection are integrated into a system.

The system demonstrates how the combination of real time data and intelligent decision making can transform an effective financial protection system to a user-friendly system. The key contribution of this work lies in its hybrid nature of incorporating environmental intelligence, user behaviour analytics and automated processes to deliver timely financial help in the event of an incident.

The proposed approach is a good representation of the dynamic nature of the gig economy as with the aid of real time weather information, user behaviour patterns and contextual clues, a risk index is generated. This will enable the system to detect potential loss of income but also anticipate and suggest approaches to the Income Protection Mode in the process of risking the risks.

Further, the addition of a multi-signal fraud processing engine will ensure the system is safe, secure and reliable in terms of fraudulent claims but also offer a seamless experience for the users. The system has experimentally demonstrated high efficiency in terms of response time and almost real time claim processing and payout simulations. The system is extendable and modular and it is possible to add even more advanced machine learning models such as gradient boosting and time-series networks in the system in the next iterations.

At the same time, there are some limitations in the system, such as using external data sources and testing on simulated datasets which might affect the performance in the real world. In terms of future work, it can be extended by incorporating fully trained machine learning models, blockchain-based claim verification system to guarantee quality and transparent claims management, and mobile apps to make it more user-friendly.

And collaborations with gig providers and financial services providers will allow for practical, large-scale deployments. Overall, NexaShift is a significant step towards the establishment of smart, autonomous and reliable financial protection systems, and the chances to help millions of gig workers around the world.

REFERENCES

[1] V. De Stefano, "The Rise of the 'Just-in-Time Workforce': On-Demand Work, Crowdwork, and Labor Protection in the Gig Economy," *Comparative Labor Law & Policy Journal*, vol. 37, no. 3, pp. 471–504, 2016.

[2] A. Sundararajan, *The Sharing Economy: The End of Employment and the Rise of Crowd-Based Capitalism*. Cambridge, MA, USA: MIT Press, 2016.

[3] S. Tesselaar and M. Botzen, "Parametric Insurance for Weather Risks: A Review," *Climate Risk Management*, vol. 33, pp. 100–115, 2021.

[4] World Bank, "Parametric Insurance Against Natural Disasters," Washington, DC, USA, Tech. Rep., 2020.

[5] Swiss Re Institute, "Innovations in Parametric Insurance," Zurich, Switzerland, Tech. Rep., 2022.

[6] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining (KDD)*, 2016, pp. 785–794.

[7] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[8] R. Bolton and D. Hand, "Statistical Fraud Detection: A Review," *Statistical Science*, vol. 17, no. 3, pp. 235–255, 2002.

[9] V. Chandola, A. Banerjee, and V. Kumar, "Anomaly Detection: A Survey," *ACM Computing Surveys*, vol. 41, no. 3, pp. 1–58, 2009.

[10] J. West and M. Bhattacharya, "Intelligent Financial Fraud Detection: A Comprehensive Review," *Computers & Security*, vol. 57, pp. 47–66, 2016.

[11] M. Zaharia et al., "Apache Spark: A Unified Engine for Big Data Processing," *Communications of the ACM*, vol. 59, no. 11, pp. 56–65, 2016.

[12] P. Domingos, "A Few Useful Things to Know About Machine Learning," *Communications of the ACM*, vol. 55, no. 10, pp. 78–87, 2012.

[13] D. Silver et al., "Mastering the Game of Go with Deep Neural Networks and Tree Search," *Nature*, vol. 529, pp. 484–489, 2016.

[14] J. Manyika et al., "The Future of Work in the Digital Age," McKinsey Global Institute, Tech. Rep., 2017.

[15] OpenWeatherMap, "Weather Data API Documentation," 2023.

[16] Central Pollution Control Board, "National Air Quality Monitoring Programme," Govt. of India, 2022.

[17] N. Kshetri, "Blockchain's Roles in Strengthening Cybersecurity and Protecting Privacy," *Telecommunications Policy*, vol. 41, no. 10, pp. 1027–1038, 2017.

[18] D. Bertsimas and R. Freund, *Data, Models, and Decisions: The Fundamentals of Management Science*. Boston, MA, USA: Cengage Learning, 2020.

[19] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 3rd ed. Burlington, MA, USA: Morgan Kaufmann, 2011.

[20] K. Murphy, *Machine Learning: A Probabilistic Perspective*. Cambridge, MA, USA: MIT Press, 2012.