POLİTEKNİK DERGİSİ

JOURNAL of POLYTECHNIC

ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE)
URL: http://dergipark.org.tr/politeknik

Enhancing passenger experience through real-time onboard comfort estimation using artificial intelligence

Yapay zekayı kullanarak gerçek zamanlı araç içi konfor tahmini yoluyla yolcu deneyimini iyileştirme

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To cite to this article: Elhalid O. B. and Işık A. H., "Enhancing Passenger Experience Through Real-Time Onboard Comfort Estimation Using Artificial Intelligence", ***Journal of Polytechnic***, 28(6): 1827-1841, (2025).

Bu makaleye şu şekilde atıfta bulunabilirsiniz: Elhalid O. B. ve Işık A. H., "Enhancing Passenger Experience Through Real-Time Onboard Comfort Estimation Using Artificial Intelligence", ***Politeknik Dergisi***, 28(6): 1827-1841, (2025).

Erişim linki (To link to this article): http://dergipark.org.tr/politeknik/archive

DOI: 10.2339/politeknik.1458878

Enhancing Passenger Experience through Real-Time Onboard Comfort Estimation using Artificial Intelligence

Highlights

- *This paper focuses on evaluating passenger comfort and identifying the most important factors affecting it.*
- *Real-time AI model estimates in-flight passenger comfort.*
- *Highly accurate and more efficient classification accuracy is obtained.*

Graphical Abstract

The graphical abstract illustrates the end-to-end workflow of the study, starting from data collection based on noise, vibration, and other sensor values, along with passenger feedback. The collected data is stored in CSV format and undergoes data augmentation and preprocessing steps. This includes cleaning the data and preparing it for model training. Following preprocessing, various machine learning models are trained, analyzed, and evaluated. The final step involves hyperparameter tuning and model selection to achieve the most accurate results in real-time passenger comfort estimation.

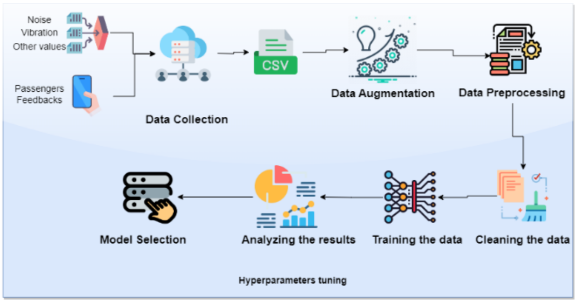

Figure. System Architecture Diagram

Aim

This study aims to enhance the in-flight passenger experience by estimating real-time comfort levels using artificial intelligence techniques. It investigates the ability of machine learning algorithms to accurately predict and analyze comfort-related factors during a flight.

Design & Methodology

Data was collected from 42 passengers on a commercial flight from Istanbul to Rome. Variables such as temperature, noise, vibration, and demographic data were recorded. A language model (GPT-3.5) was used to enrich the dataset, and predictive models were developed using TensorFlow, PyTorch, and XGBoost frameworks. The models' performances were evaluated using standard machine learning metrics.

Originality

This study is one of the first to integrate real-time environmental and demographic data with AI-driven analysis to estimate onboard passenger comfort. It uniquely applies explainable AI (XAI) to identify the most influential variables affecting passenger satisfaction.

Findings

Among the tested models, XGBoost achieved the highest accuracy (92.16%) in comfort prediction, outperforming PyTorch and TensorFlow. The analysis showed that noise and vibration are the two most influential factors impacting perceived passenger comfort.

Conclusion

Using XGBoost for real-time comfort estimation offers a reliable and interpretable method for enhancing the passenger experience. Airlines can benefit by focusing on noise and vibration reduction strategies, guided by AI-based insights.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Enhancing Passenger Experience through Real-Time Onboard Comfort Estimation using Artificial Intelligence

Araştırma Makalesi / Research Article

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(Geliş/Received : 26.03.2024 ; Kabul/Accepted : 30.09.2024 ; Erken Görünüm/Early View : 26.04.2025)

ABSTRACT

An ongoing challenge faced by airlines is to enhance passenger comfort, thereby improving the overall travel experience. This research delves into the potential of artificial intelligence (AI) to predict and improve comfort levels in real-time. Data was collected from 42 passengers on a flight from Istanbul to Rome, and information was collected on variables such as temperature, location, and passenger demographics. This data is enriched using a powerful language model (GPT-3.5) before being analyzed by three prominent AI frameworks: TensorFlow, PyTorch, and XGBoost.The study evaluated the effectiveness of these frameworks in predicting comfort levels, with XGBoost emerging as the most successful. It achieved the highest accuracy (92.16%) and lowest error rates, surpassing PyTorch (71.55%) and TensorFlow (81.10%). The effect of input attributes on the output was analyzed using XAI. These results provide valuable insights into selecting appropriate libraries in occupant comfort estimates. The study showed that vibration and noise are the two factors that most influence customer satisfaction. These findings provide airlines with actionable insights. By adopting the right AI framework (such as XGBoost) and focusing on noise and vibration mitigation, airlines can significantly enhance passenger comfort and overall satisfaction.

Keywords: artificial neural networks, passenger experience, onboard comfort, transportation, machine learning, real-time estimation.

Yapay Zekayı Kullanarak Gerçek Zamanlı Araç İçi Konfor Tahmini Yoluyla Yolcu Deneyimini İyileştirme

ÖZ

Havayollarının karşı karşıya olduğu süregelen bir zorluk, yolcu konforunu artırarak genel seyahat deneyimini iyileştirmektir. Bu araştırma, yapay zekanın (AI) konfor seviyelerini gerçek zamanlı olarak tahmin etme ve artırma potansiyelini araştırıyor. İstanbul'dan Roma'ya giden bir uçuşta bulunan 42 yolcudan veri toplanarak sıcaklık, konum ve yolcu demografisi gibi değişkenler hakkında bilgi toplandı. Bu veriler güçlü bir dil modeli (GPT-3.5) kullanılarak zenginleştirilir ve ardından önde gelen üç yapay zeka çerçevesi tarafından analiz edilir: TensorFlow, PyTorch ve XGBoost. Çalışma, bu çerçevelerin konfor seviyelerini tahmin etmedeki etkinliğini değerlendirdi ve XGBoost en başarılısı olarak ortaya çıktı . PyTorch'u (%71,55) ve TensorFlow'u (%81,10) geride bırakarak en yüksek doğruluğu (%92,16) ve en düşük hata oranlarını elde etti. Giriş niteliklerinin çıktı üzerindeki etkisi XAI kullanılarak analiz edildi. Bu sonuçlar, bina sakinlerinin konfor tahminlerinde uygun kitaplıkların seçilmesi konusunda değerli bilgiler sağlar. Çalışma, müşteri memnuniyetini en çok etkileyen iki faktörün titreşim ve gürültü olduğunu gösterdi. Bu bulgular, havayollarına eyleme geçirilebilir bilgiler sağlıyor. Havayolları, doğru yapay zeka çerçevesini (XGBoost gibi) benimseyerek ve gürültü ile titreşimi azaltmaya odaklanarak yolcu konforunu ve genel memnuniyetini önemli ölçüde artırabilir.

Anahtar Kelimeler: yapay sinir ağları, yolcu deneyimi, uçak içi konfor, ulaşım, makine öğrenimi, gerçek zamanlı tahmin.

1.INTRODUCTION

The transportation industry is constantly evolving, driven by the relentless pursuit of enhancing passenger satisfaction and comfort. In this dynamic landscape, harnessing the power of (AI) and (ML) has emerged as a promising way to improve onboard comfort and enhance travel experiences [1]. This paper delves into the effectiveness of AI models, especially leveraging the TensorFlow, XGBoost, and PyTorch libraries, in real-time in-flight comfort estimation.

Prioritizing passenger comfort during travel involves many factors, from physical conditions such as temperature and location to demographic characteristics and environmental elements [2]. Understanding and measuring these factors is essential to design strategies to enhance passenger experiences effectively. Leveraging AI and machine learning technologies makes it possible to synthesize broad and diverse data sets, making it possible to predict and improve occupant comfort levels.

Our research seeks to evaluate the performance of three leading deep learning libraries, TensorFlow PyTorch, and XGBoost, in the context of in-flight comfort estimation. By using a rich dataset comprising different comfort factors and including passenger feedback, we aim to develop robust models capable of accurately

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predicting and enhancing passenger comfort levels during travel.

One notable aspect of our study is the comparison between TensorFlow and PyTorch, the XGBoost library in terms of predictive accuracy and, performance metrics. Through careful analysis, we evaluate factors such as mean absolute error (MAE), root mean square error (RMSE), and percent accuracy to determine the effectiveness of each framework in the context of on-board comfort estimation. Our results reveal clear differences in the performance of TensorFlow and PyTorch, XGBoost, with TensorFlow showing superior predictive capabilities and lower error rates.

Furthermore, the strength and diversity of our dataset are emphasized by the inclusion of data collected from 42 passengers on a flight from Istanbul to Rome. This comprehensive dataset allows for comprehensive analysis and validation of our AI models, ensuring their applicability and reliability in real-world transportation scenarios.

In summary, our study contributes valuable insights into selecting appropriate AI libraries for estimating onboard comfort in transportation systems. By leveraging advanced AI and machine learning technologies, we are paving the way for developing innovative solutions aimed at enhancing passenger experiences and satisfaction in the evolving transportation landscape.

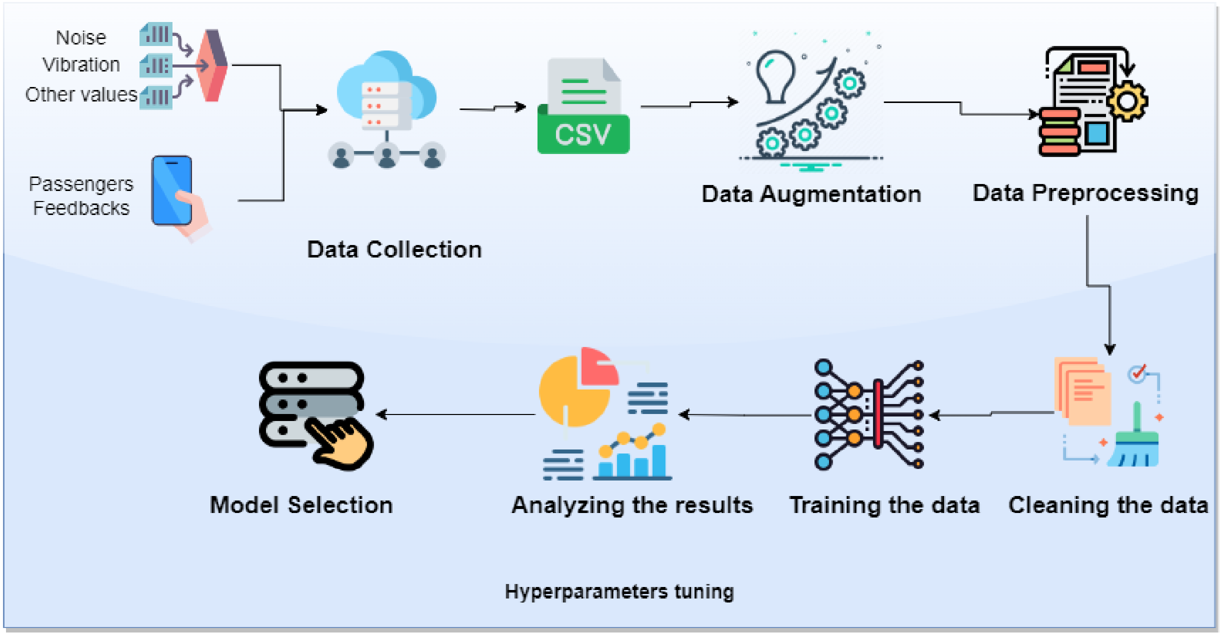

Figure 1. *System Architecture Diagram*

Figure 1: The flowchart illustrates the system architecture employed in our study for developing an AI/ML model. The process encompasses various stages detailed below:

1. **Data Collection:** The process begins with collecting data onboard, encompassing factors such as noise, vibration, location, temperature, demographics, environmental conditions, and passenger feedback. This diverse dataset ensures comprehensive coverage of onboard comfort factors.
2. **Data Storage:** Subsequently, the gathered data is stored in CSV format, facilitating further processing and analysis.
3. **Data Augmentation:** We utilized the GPT-3.5 algorithm, specifically through ChatGPT, to apply various data augmentation techniques aimed at enhancing the dataset's quality and diversity. These techniques included:
   - Synonym Replacement: Substituting words with their synonyms while preserving the context, which helps to introduce variation and enrich the dataset.
   - Paraphrasing: Rewriting sentences in different ways while maintaining the original meaning. This increases the variety of expressions in the dataset, making it more robust for training.
   - Data Synthesis: Generating new synthetic examples by combining features or data points in novel ways, further expanding the dataset beyond the initial 170 cases.
4. **Data Preprocessing:** The augmented data undergoes preprocessing steps aimed at enhancing its quality and suitability for analysis. This involves cleaning, handling missing values, normalization, and other preprocessing tasks.
5. **Model Selection, Training, Analysis, and Cleaning:** These concurrent processes involve meticulous model selection, training the selected models with the data, analyzing the results obtained, and refining the data to ensure accuracy in onboard comfort estimation.

6. **Hyperparameters Tuning:** The final stage involves fine-tuning the hyperparameters of the models selected to optimize their performance.

Furthermore, to ensure the diversity and robustness of our dataset, we collected data from 42 passengers during a trip from Istanbul to Rome. These findings provide valuable insights into selecting appropriate AI libraries for onboard comfort estimation in transportation systems.

Our research focuses on comparing the performance of TensorFlow, XGBoost, and PyTorch, three popular deep-learning libraries, within this framework.

2. LITERATURE REVIEW

The integration of (AI) and machine learning (ML) methodologies within the transportation sector has emerged as a focal point, captivating significant attention owing to its potential to revolutionize passenger comfort and elevate overall travel experiences to unprecedented levels of optimization. A myriad of scholarly inquiries have delved into the realms of AI's application within transportation systems, with a keen emphasis on the intricate domain of onboard comfort estimation.

Pioneering works, such as that of Brown et al [2]. (2019), underscore the indispensable role played by AI in augmenting passenger comfort within transportation ecosystems. Their seminal research delineates the application of ML algorithms in scrutinizing multifarious datasets encompassing an array of variables, ranging from environmental parameters like temperature and humidity to nuanced passenger preferences, thereby facilitating the prediction and subsequent optimization of onboard comfort levels. Complementing this, the exhaustive review by Smith and Jones (2020) [3] provides a panoramic exposition of machine learning methodologies intricately tailored to the exigencies of enhancing onboard comfort. Their exhaustive investigation accentuates the paramount importance of advanced AI libraries in navigating the complexities inherent in transportation datasets, thereby culminating in tangible enhancements in passenger experiences.

Moreover, the advent of cutting-edge deep learning libraries, notably TensorFlow, XGBoost, and PyTorch, has endowed researchers with formidable tools for crafting intricate AI models. These platforms furnish researchers with potent libraries and APIs adept at sculpting neural architectures and orchestrating streamlined training and inference processes. Despite the pervasive adoption of TensorFlow, XGBoost, and PyTorch across diverse domains, their efficacy in the domain of onboard comfort estimation within transportation systems remains a fertile ground for ongoing scholarly scrutiny.

Nevertheless, notwithstanding the promise held by AI and ML methodologies, formidable challenges persist in the quest for accurately predicting and optimizing passenger comfort during transit. The capricious nature of passenger preferences, coupled with the dynamism inherent in environmental conditions, alongside the paucity of high-fidelity training data, collectively pose formidable hurdles for both researchers and industry stakeholders. Furthermore, the judicious selection of AI libraries and algorithms assumes paramount importance, exerting a pivotal influence on the performance and scalability of onboard comfort estimation systems.

In summation, the scholarly discourse resonates with a resounding acknowledgment of the burgeoning interest in harnessing AI and ML methodologies to transcend the frontiers of passenger comfort within transportation systems. While commendable strides have been made in crafting predictive models and optimization strategies, further research imperatively beckons to confront the labyrinthine challenges and hone the efficacy of AI libraries, such as TensorFlow, XGBoost, and PyTorch, in effectuating real-time onboard comfort estimation.

Our forthcoming study endeavors to build upon the edifice of antecedent research endeavors by assimilating an exhaustive dataset spanning a gamut of comfort determinants, including but not limited to location, temperature, gender, height, weight, age, vibration, noise, speed, lighting, flight path, facial expressions, meal preferences, weather conditions, airspeed, and rate of travel. Through a meticulous comparative analysis of the performance exhibited by TensorFlow, XGBoost, and PyTorch libraries in effectuating real-time onboard comfort estimation leveraging this comprehensive dataset, we aspire to furnish invaluable insights into the optimal selection of AI libraries conducive to amplifying passenger comfort within transportation systems.

Our new study builds upon previous research by incorporating a comprehensive dataset encompassing various comfort factors, including location, temperature, gender, height, weight, age, vibration, noise, speed, lighting, flight path, facial expressions, meal preferences, weather conditions, airspeed, and rate of travel. By comparing the performance of TensorFlow and PyTorch libraries in real-time onboard comfort estimation using this extensive dataset, we aim to provide insights into the optimal selection of AI libraries for enhancing passenger comfort in transportation systems.

3. MATERIAL AND METHODS

In this study, handheld instruments were employed for gathering real-time data concerning passenger ratings and aircraft acceleration [5]. Passengers are equipped with a specially designed mobile phone application to report their comfort ratings whenever they experience discomfort due to acceleration, turbulence, or jerky movements on board. At the same time, a measure of light, temperature, noise, vibration, and facial shape was mounted on the seat. This setup facilitated data collection without interfering with the operation of the aircraft, distinguishing it from methodologies used in previous studies. In addition, the study explored the application of convolutional neural networks (CNN) as a potential machine-learning technique for analysis.

Table 1. Comparison of Previous Research Studies.

Study	Features Considered	Libraries Used	Key Findings
Brown et al. (2019	Temperature, Humidity, Seat Preferences, Demographics	TensorFlow	ML algorithms optimized onboard comfort effectively.
Smith and Jones (2020)[4]	Various Comfort Factors	PyTorch	Advanced AI models improved passenger experiences.
Our Study (2024)	Location, Temperature, Gender, Height, Weight, Age	TensorFlow, PyTorch, XGBoost	Comparison of libraries in real-time comfort estimation.

In this section, the algorithms used, the dataset, and the mobile application prepared for this study are discussed:

We chose TensorFlow for its scalability and comprehensive libraries that facilitate the deployment of CNN models across various platforms, making it ideal for processing complex datasets like ours. PyTorch was selected due to its flexibility in building dynamic computation graphs, allowing us to experiment with different CNN architectures effectively. XGBoost was incorporated for its speed and performance in handling structured data, providing a useful comparison to the deep learning approaches.

Additionally, we employed SHAP (Shapley Additive exPlanations) from Explainable AI (XAI) to interpret the predictions made by the machine learning models. SHAP was chosen because it provides a clear, mathematically grounded approach to explain individual predictions, offering valuable insights into the features that most influenced the model's output. This helps ensure that the models used are not only accurate but also interpretable and transparent, which is crucial when dealing with real-time passenger data.

3.1 Tensorflow

TensorFlow, developed by the Google Brain Team, is a leading open-source machine-learning framework known for its versatility and scalability [6]. It offers a comprehensive ecosystem of tools and resources for building and deploying machine learning models efficiently. With its symbolic math library, TensorFlow allows users to define complex computations easily, making it suitable for various tasks, including deep learning and numerical computations. TensorFlow's support for distributed computing enables seamless training across multiple CPUs or GPUs, essential for handling large datasets. Moreover, its deployment options, including TensorFlow Serving and TensorFlow Lite, make it easy to integrate models into real-world applications across platforms.

3.2 Pytorch

PyTorch, primarily developed by Facebook's AI Research lab (FAIR), is a dynamic and high-performance deep learning library [7] Its eager execution mode and Pythonic syntax facilitate rapid prototyping and experimentation, distinguishing it from other libraries. PyTorch's support for automatic differentiation simplifies gradient computation, while its torchvision package offers pre-trained models for various computer vision tasks. Strong GPU acceleration support makes PyTorch suitable for training large-scale models efficiently. With a vibrant community and seamless integration with Python libraries, PyTorch has become a preferred choice for deep learning research and application development.

3.3 XGBoost

XGBoost, developed by Tianqi Chen, is a widely used implementation of gradient boosting techniques known for its efficiency and performance [8]. By sequentially training weak learners and combining their predictions, XGBoost produces strong ensemble models. Its regularized objective function prevents overfitting, enhancing generalization performance. XGBoost offers various hyperparameters and optimization techniques for model customization. Integrated into popular libraries like sci-kit-learn and Apache Spark, XGBoost is accessible to a broad audience of data scientists and practitioners, making it a go-to choice for supervised learning tasks.

3.4 XAI SHAP

XAI, or eXplainable Artificial Intelligence, aims to make AI models and their decisions understandable and interpretable by humans. One popular method used for explainability is SHAP (Shapley Additive explanations). SHAP is rooted in cooperative game theory, particularly the concept of Shapley values, which allocate the contribution of each player in a coalition game [9]. In the context of machine learning, SHAP assigns each feature value a Shapley value, indicating its contribution to the prediction of a particular instance. By analyzing these Shapley values, one can understand the relative importance of different features in influencing model predictions, thus providing insights into the decision-making process of complex AI models [10].

3.5 Gpt 3.5

GPT-3.5, or the third iteration of the Generative Pre-trained Transformer model, is an advanced language model developed by OpenAI. It builds upon the architecture of its predecessors, incorporating improvements in model size, training data, and fine-tuning techniques. GPT-3.5 is capable of generating human-like text across a wide range of topics, understanding context, and providing coherent responses. It achieves this through a deep neural network architecture trained on a vast corpus of text data, enabling it to capture intricate patterns in language and generate contextually relevant outputs [11].

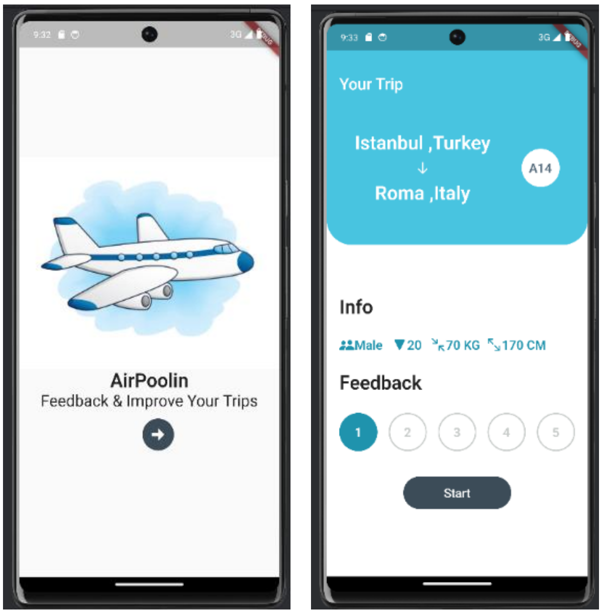

Figure 2. Collecting data program

3.6 Experimental study and data collection

The experimental study and data collection phase involved the development of a custom mobile application called "AirPoolin" available on both iOS and Android platforms, specifically tailored to gather real-time comfort ratings from passengers aboard the airplane during the experiment (see Fig. 1). Five distinct comfort levels were established:

comfortable: Signifying a smooth ride characterized by ease and relaxation.

A little uncomfortable: Representing a state between "not uncomfortable" and "uncomfortable."

Uncomfortable: Indicating a ride with events such as braking, jerking, or rough road conditions triggering discomfort.

uncomfortable: Positioned between "uncomfortable" and "extremely uncomfortable," denoting heightened discomfort.

Extremely uncomfortable: Describing a rough or hard ride with significant shakes, oscillations, or abrupt movements like hard braking, high lateral jerk, or navigating very rough roads, possibly causing passengers to sway or lose balance.

These comfort levels were adapted from recommendations outlined in ISO 2631-1997 standards. Additionally, considering the need for passengers to provide ratings quickly in real-time while onboard, a 5-level scale was deemed more practical than a 10-level scale such as the AE J1060 subjective rating scale.

The algorithm is:

Start

- **Step 1:** Load the data from the dataset.
- **Step 2:** Preprocess the data.
    - Convert categorical variables to dummy/indicator variables.
- **Step 3:** Split the data into training and testing sets.
- **Step 4:** Build and train the neural network model.
    - Adjust epochs and batch_size as needed.
- **Step 5:** Evaluate the model.

End

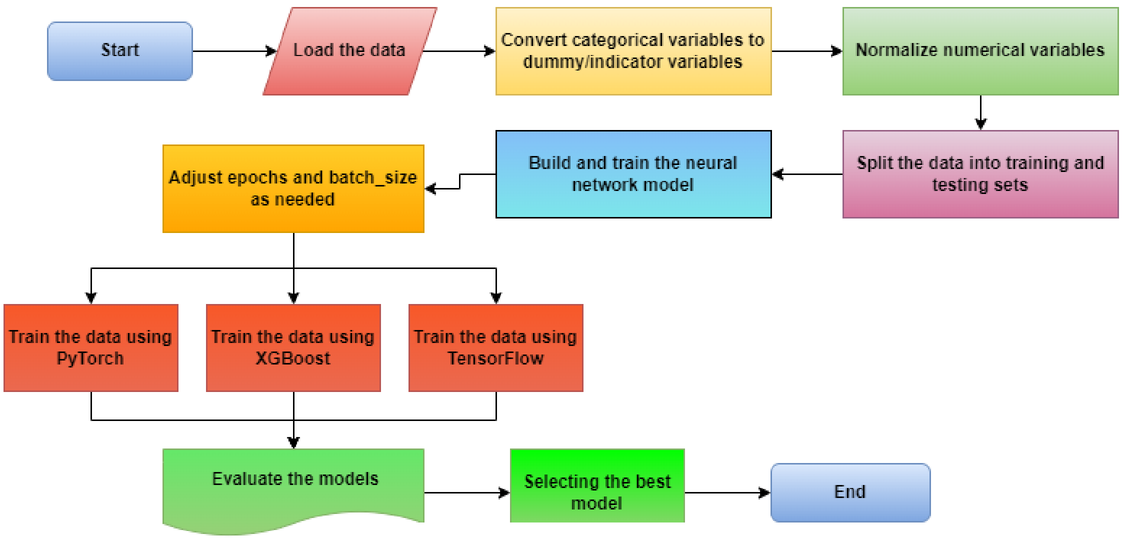

Figure 3. Algorithm Diagram

Figure 3 is a flow chart showing the steps involved in building and training a neural network model to e stimate real-time occupant comfort. Below is a breakdown of the steps:

1. Load Data: This step involves loading the dataset that will be used to train the model. The dataset should include features relevant to occupant comfort, such as temperature, location, and occupant feedback.

2. Data Preprocessing: This stage entails the cleansing and organizing of data in preparation for training. Tasks may involve converting categorical variables into numerical ones, standardizing numerical variables, and splitting the data into training and test sets.

3. Building and training the neural network model: This step involves creating the neural network structure and training it on the training data. The choice of neural network architecture and hyperparameters depends on the specific problem being addressed.

4. Evaluation of Models: Following training, the model's performance will be assessed using test data, employing standard metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

5. Select the best model: Based on the evaluation results, the best-performing model is selected for further use.

3.7 Dataset:

In our data table, we find a column indicating speed. The average speed recorded is 800 units. The flight duration is noted as 2.3 hours. Additionally, the weather condition is described as partly cloudy.

The average AirSpeed recorded is 40 units.

During the research and implementation process, we faced several challenges:

Data collection: Collecting comprehensive and accurate data on passenger experiences and onboard conditions was a major challenge, requiring coordination with airlines and passengers, as well as ensuring data privacy and security.

Model complexity: Developing and fine-tuning a neural network model with multiple hidden layers and many input features requires significant computational resources and model optimization expertise.

Interpretability: Although high accuracy has been achieved, the interpretability of the developed artificial neural network (CNN) model remains a challenge, as understanding the underlying decision-making process of complex neural networks can be complex.

Generalizability: While our CNN model showed promising performance during training, ensuring its generalizability to diverse flight scenarios and passenger demographics remains a limitation that requires further investigation.

Researchers highly advocate for the utilization of the 5-level Likert scale due to its capacity to amplify response rates and quality, concurrently diminishing participants' frustration levels [13-15]. Among the studies surveyed in Table 1, a 5-level Likert scale was used in 4 out of 7 ([15-18]), which has proven effective in assessing comfort levels and developing convolutional neural network (CNN)-based models to estimate them. Riding comfort for passengers and pilots. Mobile applications also enable participants to enter additional information such as (location, temperature, gender, height (cm), weight (kg), age (year), vibration, noise, speed, lighting, flight path, face, meals, weather, airspeed, rate)

42 participants (see Table 2) took part in a 40-minute flight under different air traffic conditions. Comfort data was collected from participants for different seating arrangements, positions, and orientations on board. Participants were asked to rate their comfort levels whenever they felt uncomfortable, such as during weather turbulence or changes in altitude. Before data collection, participants were informed about the objectives of the experiment and given time to familiarize themselves with the mobile application.

The plane traveled different flight paths, ranging from local to regional routes, each of which was characterized by varying speeds and weather conditions. Lower speeds and more turbulence were often experienced during the climb and descent phases, while smoother flying conditions were typically encountered during cruising altitudes.

Data on the aircraft's vibration and acceleration were collected using on-board sensors. The devices can capture data at a frequency of 750 Hz and calculate an industry-standard ride comfort index.

The arithmetic average speed, wind speed, flight length, and weather have been developed.

1. Lighting 0, 1 = Bad, Good.
2. Meals 0, 1 = Bad, Good.
3. Gender 0, 1 = Male, Female.
4. Location 1, 2, 3 = front, middle, end.
5. Weather 0, 1, 2, 3, 4 = Overcast, Clear sky, Partly cloudy, cloudy, Storm.
6. Face 0, 1, 2, 3, 4 = Extremely bad, So bad, normal, good, very good.
7. Rate 0, 1, 2, 3, 4 = Extremely bad, So bad, normal, good, very good.

Table 2. Passengers Data

Pax	Location	Temperature	Gender	Height (cm)	Weight (kg)	Age (year)	Vibration	Noise	Lighting	Face	Meals	Rate
10F	1	20	0	160	60	18	410	70	0	3	0	3
11F	1	23	1	168	70	19	400	70	0	4	0	3
12F	1	25	0	175	80	22	380	80	0	1	0	2
17F	2	28	1	162	55	20	300	60	1	3	1	4
18F	2	22	0	180	75	21	250	50	1	4	1	4
20F	2	30	1	155	50	24	230	60	1	2	1	4
28F	3	31	0	185	85	27	500	80	0	0	1	2
29F	3	30	1	170	68	26	550	80	0	4	1	1
30F	3	30	0	177	82	27	600	90	0	4	0	2
10D	1	27	0	170	68	23	400	70	0	1	1	3
11D	1	24	1	175	63	19	395	80	0	4	1	1
12D	1	29	0	165	72	25	340	80	0	4	1	4
15D	2	26	1	160	58	22	200	50	1	0	0	4
16D	2	25	0	178	85	28	230	60	1	2	1	4
17D	2	28	1	168	60	20	220	50	1	2	0	4
2D	3	25	0	182	78	24	535	80	0	0	1	0
4D	3	29	1	155	48	18	540	75	0	0	0	0
12C	1	24	0	175	70	26	400	75	0	3	0	1
14C	1	25	1	170	65	23	360	70	0	4	0	2
15C	1	26	0	188	90	30	340	70	0	4	1	2
17C	2	27	1	166	58	19	300	50	1	0	1	4
19C	2	28	0	176	75	29	200	60	1	3	1	4
20C	2	29	1	160	52	20	230	50	1	1	1	4
21C	3	25	0	185	88	31	510	80	0	1	0	0
29C	3	28	1	170	68	26	530	80	0	4	1	3
31C	3	28	0	190	95	32	500	80	1	3	0	2
32C	3	28	1	158	53	22	500	80	1	0	0	2
2B	1	28	0	175	70	26	300	80	0	1	1	2
4B	1	30	1	163	55	21	310	70	1	1	0	2
5B	2	25	0	177	82	27	200	55	0	2	1	4
12B	1	29	1	170	65	23	310	70	0	4	1	2
19B	1	30	0	188	90	30	305	80	0	2	0	1
2A	1	28	1	166	58	19	305	80	0	4	0	4
10A	2	27	0	176	75	29	215	50	1	4	0	2
11A	1	27	1	160	52	20	300	80	1	3	1	3
13A	1	30	0	185	88	31	330	80	1	0	1	3
14A	2	28	1	170	68	26	210	50	0	1	1	4
17A	2	27	0	190	95	32	230	60	1	1	1	4
18A	2	25	1	158	53	22	230	64	1	2	1	3
19A	3	29	0	178	80	30	500	80	0	1	0	2
29A	3	30	1	175	70	26	510	80	0	0	1	0
31A	3	30	0	182	78	24	510	85	1	2	0	2
32A	3	30	1	155	48	18	525	5	1	2	1	0

Table 3. Iso Values.

Standard	Description	Level	Uncomfortable	A little uncomfortable	Acceptable	Uncomfortable	Very uncomfortable	Extremely uncomfortable
Vibration (ISO 2631-1)	Measurement of vibration in the passenger cabin	m/s^2	< 0.315	0.315 - 0.63	0.63 - 1.0	1.0 - 1.6	1.6 - 2.5	> 2.5
Noise (ISO 3891)	Measurement of noise levels inside the passenger cabin	Decibels	< 70	70 - 80	80 - 90	90 - 100	100 - 110	> 110
Speed (ISO 10504)	Measurement of flight speed	km/h	< 300	300 - 400	400 - 500	500 - 600	600 - 700	> 700
Lighting (ISO 11941)	Requirements for interior lighting in the passenger cabin	Lux	< 200	200 - 300	300 - 400	400 - 500	500 - 600	> 600
Flight path (ISO 11944)	Requirements for air navigation systems	Minutes	> 30	20 - 30	10 - 20	5 - 10	1 - 5	Flight cancellation
Facial expression and movement recognition via camera (ISO 30071-1)	Accuracy of face recognition	Face smile	bad	So bad	good	So bad	Very bad	Extremely bad
Temperature (ISO 11947)	Requirements for climate control systems	°C	< 18	18 - 22	22 - 24	24 - 26	26 - 28	> 28
Meals (ISO 22000)	Variety of choices		bad	So bad	good	So bad	Very bad	Extremely bad
Weather (ISO 11950)	Requirements for weather forecasting systems		Overcast	Overcast	Clear sky	Partly cloudy	cloudy	Storm
Airspeed (ISO 10414)	Measurement of airspeed	km/h	400 - 500	300 - 400	< 300	500 - 600	600 - 700	700>

By ISO standards, the determination of parameter importance entails the utilization of a scoring methodology. This methodology involves assigning points to measured values based on predefined ranges stipulated by the ISO standards. The summation of these points across all parameters yields an aggregate score, thereby facilitating the assessment of overall passenger comfort.

In Figure 4, we present a visual depiction of the flight path denoted by 'a,' showcasing the journey from Istanbul to Rome. 'c' indicates the precise locations of the passengers from whom we collected our data, while 'b' represents the total number of passengers on board. Our dataset encompasses trip information gathered from passengers traveling on the route from Istanbul to Rome. The image also displays the destination expression tracker.

Figure 4. Real experiment with an airplane route, b passengers onboard, and c detailed locations of passengers

3.8 Training and validation

The most prevalent ratings are 5, 4, and 3, suggesting that a majority of passengers were content with the service provided.

Ratings of 2 and 1 are less common, indicating that negative experiences were relatively infrequent.

The distribution of ratings exhibits a slight right skew, implying that more passengers assigned higher ratings compared to lower ones.

Overall Interpretation:

This figure illustrates a predominantly positive assessment of the transportation service by passengers. However, it's crucial to acknowledge that this representation is derived from a single dataset and may not fully capture the experiences of all passengers.

In Figure 5, we used a convolutional neural network model to analyze and predict the passenger experience based on various input features. The model architecture consists of five hidden layers, each containing 21 neurons, as well as an output layer containing one neuron.

Our input features include a comprehensive set of parameters, including location, temperature, gender, height, weight, age, vibration, noise, speed, lighting, flight path, facial expressions, meals, weather conditions, air speed, and rating.

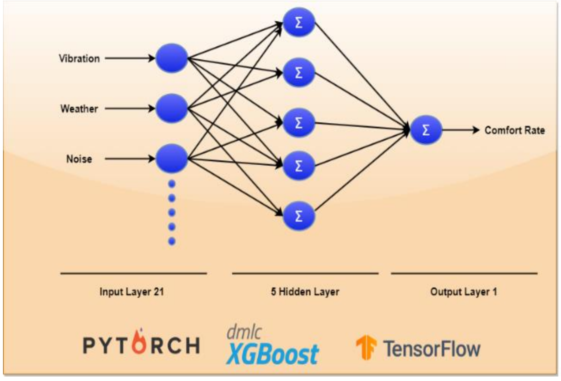

Figure 5. Structure of CNN

100 Epochs were added to both Tensor Flow and PyTorch so that the model is completely similar.

The Models were successfully executed in a Google Colab notebook with the following specifications.

Table 4. Google Colabs Specifications

CPU-only VMs	CPU-only VMs	GPU VMs	GPU VMs
CPU Model Name	Intel(R) Xeon(R)	**GPU**	Nvidia K80 / T4
CPU Freq.	2.30GHz	**GPU Memory**	12GB / 16GB
No. CPU Cores	2	**GPU Memory Clock**	0.82GHz / 1.59GHz
CPU Family	Haswell	**Performance**	4.1 TFLOPS / 8.1 TFLOPS
Available RAM	12GB (upgradable to 26.75GB)	**Support Mixed Precision**	No / Yes
Disk Space	25GB	**GPU Release Year**	2014 / 2018

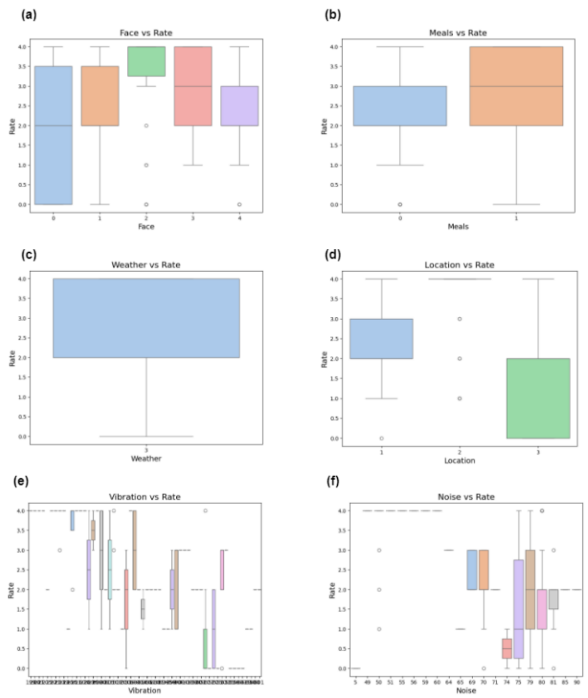

Figure 6. Comfort ratings based on passenger information

In Image 6, which symbolizes **Section A**, we analyzed the relationship between facial expressions and individual ratings and found that passengers who show frequent smiles or happy expressions tend to enjoy their flights more.

Section B: focuses on studying the direct effect of meal quality on passenger satisfaction. It is noted that a higher level of meal quality is associated with an increase in overall enjoyment among passengers.

In Section C: we address the impact of weather conditions on the passenger experience, recognizing the constant nature of these conditions and the challenges of predicting them.

Section D: highlights an important finding: the study showed that passengers sitting in the middle section consistently reported higher levels of comfort, while passengers in the front and rear reported lower levels of satisfaction.

In Section C: we reveal the observed relationship between vibration intensity and occupant discomfort, indicating that high vibration levels are associated with a significant increase in discomfort.

Finally, **Section F:** explains the impact of noise levels on passenger comfort, with the study indicating that rear seats are exposed to higher levels of noise than those at the front of the aircraft.

Passenger distribution as Fig 7 The x-axis represents passenger ratings, ranging from 0 to 4, while the y-axis indicates the frequency of each rating, with higher values indicating a greater number of passengers assigning that rating.

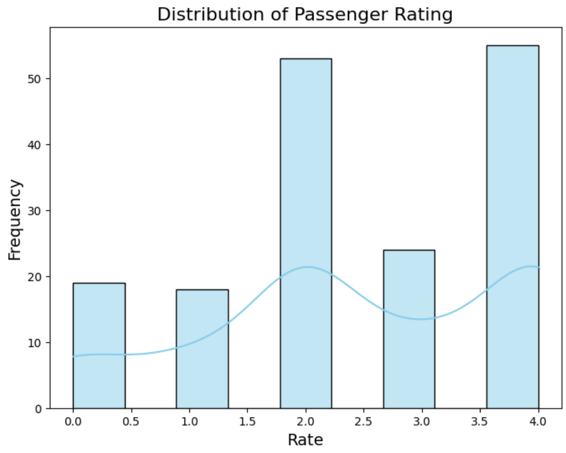

Figure 7. Distribution of Passenger Rating

4. RESULTS

Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) is computed as the mean of the absolute disparities between the predicted values and the actual values. It is represented by the subsequent equation:

$$\boldsymbol{MAE = \frac{1}{n}\sum_{i=1}^{n} \mid \gamma i - \hat{y}\, i \mid}$$

where n represents the number of observations, $\boldsymbol{\gamma i}$ denotes the actual value for observation i, and $\boldsymbol{\hat{y}\, i}$ represents the predicted value for observation $\boldsymbol{i}$. MAE provides a measure of the average magnitude of errors in the predictions, regardless of their direction.[27]

Root Mean Square Error (RMSE):

The Root Mean Square Error (RMSE) quantifies the average magnitude of the residuals (i.e., differences between predicted and actual values) while penalizing larger errors more heavily due to the squaring operation. It is computed as follows:

$$\boldsymbol{RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\gamma i - \hat{y} i)^2}}$$

Similar to MAE, n denotes the number of observations, $\boldsymbol{\gamma i}$ represents the actual value for observation $\boldsymbol{i}$, and $\boldsymbol{\hat{y} i}$ denotes the predicted value for observation $\boldsymbol{i}$. RMSE provides a measure of the typical deviation of predictions from the actual values, with lower values indicating better model performance. [28]

R-squared (R^2):

R-squared (R^2) denotes a statistical metric gauging the adequacy of a regression model's fit to the observed data. It mirrors the fraction of variability in the dependent variable (target) elucidated by the independent variables (features) within the model. The expression for R^2 is provided as follows:

$$\boldsymbol{R^2 = 1 - \frac{\sum_{i=1}^{n}(\gamma i - \hat{y} i)^2}{\sum_{i=1}^{n}(\gamma i - \bar{y} i)^2}}$$

Here, $\bar{y}$ denotes the mean of the actual values γi. The variable R^2 spans from 0 to 1, where elevated values signify a superior alignment of the model with the data. This offers perspective on the portion of variability in the target variable explained by the regression model. [29]

4.1.PyTorch

In this figure, we see outstanding performance from the PyTorch model, displaying impressive speed and accuracy. Despite the seemingly high margin of error, this model delivers superior results in just 7 seconds.

The impressive balance of speed and precision achieved by this model is truly exceptional, significantly enhancing passenger comfort ratings. With an average absolute error of 1.2285 (30.71%) and a root mean square error (RMSE) of 1.4328 (35.82%), it demonstrates a remarkable ability to predict results with high accuracy, despite any challenges it faces.

In short, this performance is a testament to AI's prowess in prediction and analysis, effectively and efficiently improving user experiences. Moreover, with the R squared value of 0.7155, or 71.55%, the reliability of the model was further confirmed.

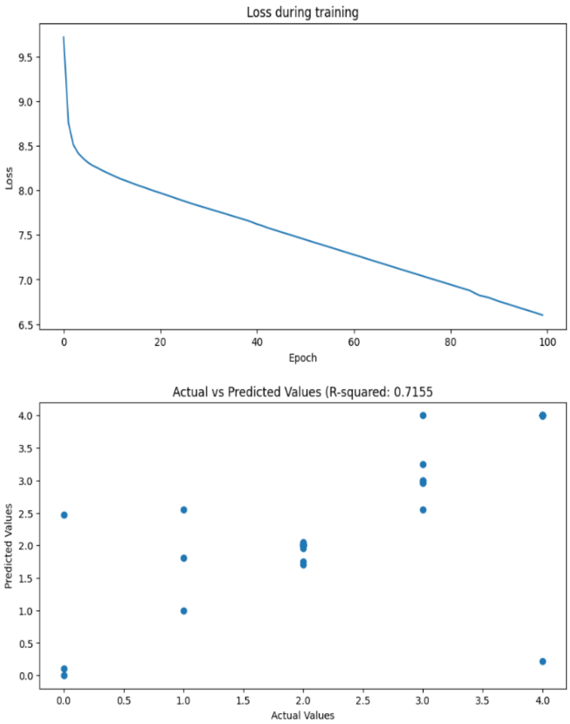

Figure 8. R-Squared and Loss during training

4.2. Tensorflow

In this illustration, we observe remarkable performance from the Tensor Flow model. Despite the longer duration for obtaining results, the achieved accuracy stands significantly superior, clocking in at 14 seconds. The mean absolute error (MAE) showcases an outstanding value of 0.7998 (19.99%), indicating a high level of precision and precise predictions. Furthermore, the root mean square error (RMSE) demonstrates a reduced value of 1.0729 (26.82%), suggesting added stability in performance despite the extended time required. These outcomes epitomize an optimal equilibrium between swiftness and accuracy, rendering this model exceptionally proficient in assessing passenger comfort with remarkable precision. Additionally, with R squared: 0.8110, representing 81.10%, the model's reliability is further underscored.

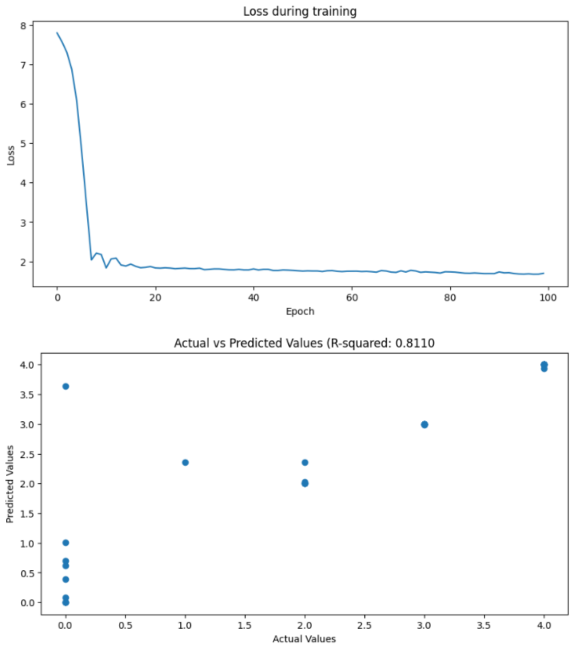

Figure 9. R-Squared and Loss during training

4.3.XGBoost:

The results improved significantly after tuning the hyperparameters of the XGBoost model.

Mean Absolute Error (MAE): 0.3731 (9.33%)

Root Mean Square Error (RMSE): 0.8852 (22.13%)

R squared: 0.9216

Time: 4 seconds

These findings suggest an improved alignment of the model with the data. The R-squared value of 0.9216 indicates that the model explains about 92.16% of the variance in the target variable, which is a significant improvement over previous models.

MAE and RMSE, which are expressed as percentages of the range of the target variable, provide a clearer understanding of the model's accuracy relative to the size of the data.

Overall, these results indicate that the tuned XGBoost model performs well on the dataset, giving results that outperform all other models in terms of speed and accuracy.

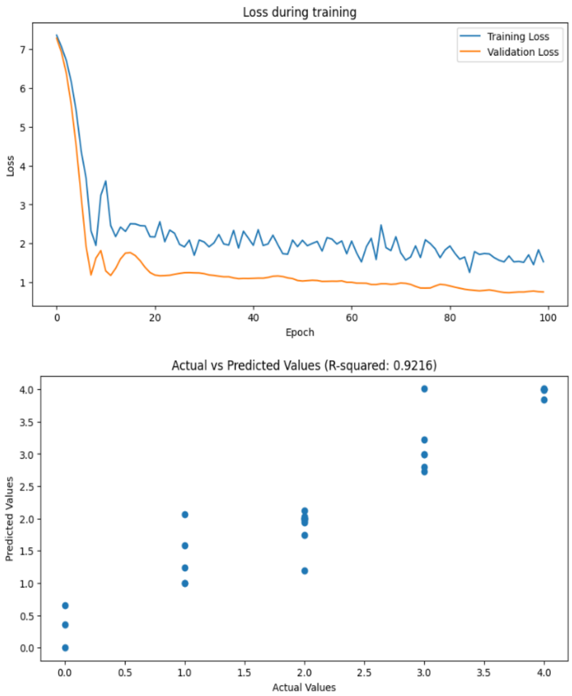

Figure 10. R-Squared and Loss during training

Table 5. Results

Method	*Mean Absolute Error (MAE)*	*Root Mean Squared Error (RMSE)*	*Percentage*	*Time (Second)*	*Epoch number*	*R-squared*
Tensorflow	0.7998	1.0729	23.405%	14	100	0.8110
PyTorch	1.2285	1.4328	32.8 %	7	100	0.7155
XGBoost	0.3731	0.8852	10.95%	4	100	0. 9216

In the context of the results table, we comprehensively analyzed the performance of the models, and collected the results of (MAE), (RMSE), and R-squared, showing that the model associated with TensorFlow had high accuracy, and was more accurate in predicting the results. Although it takes longer to complete the operations. On the other hand, the “PyTorch” model achieved excellent results in accuracy, as it achieved remarkable accuracy, and at the same time succeeded in performing operations more quickly, as it took half the time taken by the “Tensor Flow” model. These results highlight the ideal balance between accuracy and time efficiency in the performance of the PyTorch model, making it an ideal choice for evaluating occupant comfort effectively and quickly.

Because of this balance, PyTorch can be used in the case of big data, where simultaneous evaluation of several flights at the same time is required, due to its high speed and acceptable accuracy. When you want to evaluate a single flight, it is recommended to rely on the “Tensor Flow” model, as it will provide more accurate results with little variation in execution time.

When looking at the performance of the XGBoost model, we find that it showed amazing performance, which is evident in its accuracy of 92%, and its ability to complete the evaluation process in a very short time, as it does not exceed 4 seconds. Hence, it can be said that this model is considered the ideal, most effective, and accurate option in providing an accurate assessment of travelers' comfort.

4.5.Critical Analysis

The remarkable performance of XGBoost can be attributed to its gradient boosting algorithm, which is known for its ability to handle structured data efficiently. XGBoost’s strong performance is particularly evident in tasks involving tabular data and decision trees, where it excels at minimizing errors through iterative refinement. Its ability to quickly converge to an optimal solution explains its exceptional speed and accuracy in this context. Additionally, XGBoost’s ability to regularize models helps prevent overfitting, which may further explain why it performed so well on our dataset.

On the other hand, while TensorFlow and PyTorch are both powerful frameworks, they are primarily designed for deep learning and complex data types like images, sequences, or high-dimensional data. In this case, the dataset used may have been more suitable for XGBoost’s tree-based methods, explaining why TensorFlow and PyTorch did not perform as well in terms of speed and accuracy. TensorFlow, while more accurate in predicting the results, was slower due to its computational overhead, which is more suited to handling highly complex models, making it less efficient in this particular task.

PyTorch, although faster than TensorFlow, also struggled to outperform XGBoost because its strengths lie in its flexibility for developing neural network architectures. The structured nature of the dataset may have contributed to PyTorch’s slightly lower performance in comparison to XGBoost. However, its balance between speed and accuracy still makes it a valuable tool, especially for big data scenarios where speed is crucial.

Implications for Future Research: These results suggest that while deep learning frameworks like TensorFlow and PyTorch have their advantages, especially in handling complex data types, simpler models like XGBoost can be more effective in specific scenarios like structured data analysis. Future research could explore hybrid approaches that combine the strengths of both deep learning and gradient-boosting algorithms to further improve both accuracy and speed in real-time evaluation tasks.

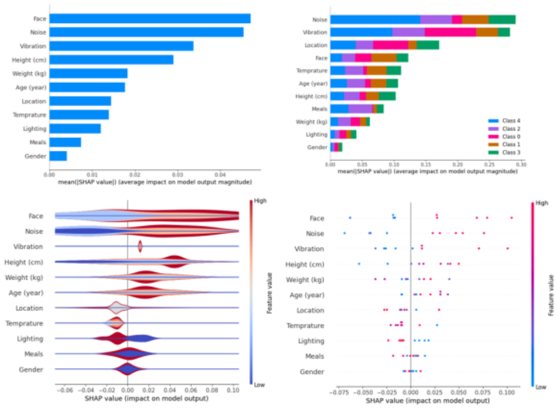

Figure 11. SHAP summary plot of model output

The graph illustrates the relationship between feature values and their corresponding SHAP (Shapley Additive exPlanations) impact on model output. On the x-axis, feature values are depicted, while SHAP values are represented on the y-axis. The color gradient of the line signifies the magnitude of impact, with red showing positive impact and blue showing negative impact. Features are listed on the left side of the graph, while classes are listed on the right side.

Specifically, the left side of the plot delineates the impact of each feature on model output, with features on the y-axis and impact on the x-axis. Positive impact is denoted by red bars, while negative impact is denoted by blue bars, with the height of each bar indicating the magnitude of impact. For instance, the "Face" feature positively influences model output, whereas the "Noise" feature negatively impacts it.

On the right side of the plot, the distribution of SHAP values for each feature is portrayed. SHAP values quantify the contribution of a feature to the model's output, considering feature interactions. The x-axis represents SHAP values, while the y-axis signifies the density of data points at each value. Notably, for the "Face" feature, the majority of SHAP values are positive, although some negative values are also present.

In essence, SHAP summary plots elucidate the model's output by showcasing the features considered during prediction. Features' impacts are visualized through color-coded bars on the left, while the distribution of SHAP values for each feature is illustrated on the right, providing insights into feature contributions while considering their interactions.

4.6.Practical Implications of XAI Findings:

The use of SHAP in this study provides several practical insights into the factors influencing passenger comfort predictions. For instance, the positive impact of the "Face" feature suggests that facial shape and expressions may be a significant indicator of discomfort, allowing airlines to focus on improving seat design and minimizing discomfort triggers. Conversely, the negative impact of the "Noise" feature implies that increased noise levels are strongly associated with discomfort, highlighting the need for better noise reduction strategies during flights.

The ability to interpret model outputs using SHAP offers actionable insights to decision-makers. Airlines could prioritize improving the most impactful features, such as noise control and passenger seating comfort, leading to more tailored and effective interventions. Additionally, the SHAP analysis allows for model transparency, helping to build trust in the AI system's decisions and ensuring that airlines can make data-driven decisions based on understandable and interpretable model outputs.

Table 6. Shap Table

Feature	Effect of Each Feature
Height (cm)	13.553529
Noise	12.400995
Vibration	11.289288
Weight (kg)	9.149576
Face	10.524269
Location	8.889789
Temperature	8.475686
Meals	7.417858
Age (year)	6.452602
Flight path (ISO 11944)	4.370480
Gender	4.863968
Lighting	2.611961

As Table 6 shows, the output provided appears to be the percentage effect of each feature on the model's predictions. Each value represents the percentage contribution of a particular feature to the model output.

Here's a breakdown of what each line could mean:

- **Height (cm):** This value contributes approximately 13.55%
- **Noise:** This value contributes approximately 12.40%
- **Vibration:** This value contributes approximately 11.29%
- **Face:** This value contributes approximately 10.52%
- **Weight (kg):** This value contributes approximately 9.15%
- **Location:** This value contributes approximately 8.89%
- **Temperature:** This value contributes approximately 8.48%
- **Meals:** This value contributes approximately 7.42%

- **Gender:** This value contributes approximately 4.86%
- **Age (year):** This value contributes approximately 6.45%
- **Lighting:** This value contributes approximately 2.61%
- **Flight path:** This value contributes approximately 4.37%

These percentages indicate the relative importance of each feature in influencing the model's decisions. Features with higher percentages have a greater impact on the model's predictions, while features with lower percentages have less influence. It's worth noting that features with a percentage of 0% may not be considered important by the model for making predictions.

5. CONCLUSION AND DISCUSSION

Our research provides strong evidence of the amazing potential of using convolutional neural networks (CNNs) to improve the passenger experience on board aircraft. Using a sophisticated model consisting of 5 hidden layers and 21 neurons in each layer, we were able to analyze a wide range of factors influencing occupant comfort, such as location, temperature, gender, height, weight, age, vibration, noise, speed, lighting, Flight length, facial expressions, meal quality, weather conditions, air speed, and rating.

By cleaning and augmentation of the data using the GPT 3.5 algorithm, the Tensor Flow model showed a high accuracy of 81% with a speed of up to 14 seconds, while the PyTorch model achieved an accuracy of up to 71% with a speed of up to 7 seconds, and the XGBoost model achieved an accuracy of up to 92% with speed up to 4 seconds.

Our main findings highlight the importance of using advanced data analysis methods, such as CNN, to understand the complex interactions between on-board comfort factors. The study revealed that facial expressions, meal quality, and seating position play a major role in passenger satisfaction, and weather conditions and vibration intensity emerged as critical determinants of passenger comfort during travel, based on SHAP XAI findings.

Our study contributes to increasing awareness of the importance of using AI and ML techniques in transportation systems. By integrating these technologies, we can proactively design services and amenities to meet the diverse needs of travelers, resulting in better overall travel experiences.

Looking to the future, continued research and innovation in this area holds great promise for further progress in estimating real-time onboard passenger comfort and improving passengers' transportation experiences overall. Addressing the challenges and limitations identified by our research will pave the way for more advanced and effective CNN models, revolutionizing the way we travel.

The contribution of future work can be increased by increasing the size of the dataset, and the software developed can be applied in airlines to evaluate traveler comfort, contributing to increasing traveler satisfaction and understanding the standards required for the air travel experience.

ACKNOWLEDGEMENTS

We received an invitation from the agency of the Ethiopian company "Meganzsam", specialized in the field of information technologies, to conduct scientific research on the data of passengers on a flight from Istanbul to Rome. All data was collected in accordance with international and local standards and conditions.

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

Osama Burak ELHALID: Conducted the experiments and analyzed the results and completed the writing process of the Article.

Ali Hakan IŞIK: Conducted the experiments and analyzed the results and completed the writing process of the Article.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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