

Future Flight Safety Monitoring: Comparison of Different Computational Methods For Predicting Pilot Performance Under Time Series During Descent By Flight Data And Eye-Tracking Data.

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Abstract. Introduction. Effective and real-time analysis of pilot performance is important for improving flight safety and enabling remote flight safety control. The use of flight data and pilot physiological data to analyse and predict pilot performance is an effective means of achieving this monitoring. **Research question.** This research aims to comparing two forecasting methods (XGBoost and Transformer) in evaluating and predicting pilot performance using flight data and eye tracking data. **Method.** Twenty participants were invited to fly an approach using instrument landing system (ILS) guidance in the Future System Simulators (FSS) while wearing Pupil-Lab eye tracker. The deviation to the desired route, the pupil diameter and the gaze positions were selected for forecasting the flight performance indicator: the difference between the aircraft altitude and the reference altitude corresponding to the ideal 3-degree glide path. Use XGBoost and the Transformer forecasting method to build the forecasting model using the data in this research and compare the accuracy and convenience of the two models. **Results & Discussion.** The result demonstrates that using XGBoost regression model had a higher prediction accuracy, (present result here) and its easier to achieve a high prediction accuracy than Transformer as Transformer forecasting method placed a high demand on debugging model and computing equipment. The deviation to desired route and the pupil diameter were more important in the XGBoost model. **Conclusion.** The use of machine learning and deep learning methods enables the monitoring and prediction of flight performance using flight data and pilot physiological data. The comparison of the two methods shows that it is not necessarily the newer and more complex technology that can build more accurate and faster prediction models, but building the right model based on the data is important for real-time flight data monitoring and prediction in the future.

Keywords: data analysis, human-machine interactions, eye-tracking data; pilot performance monitoring

1 Introduction

How to effectively monitor and predict flight performance and pilot behaviour is a major topic in future aviation safety research [1]. Remote monitoring of flight status and pilot performance with time series has become possible with improvements in transmission technology and aircraft computer power [2]. This paper aims to utilize machine learning methods to analyse flight data and eye tracking data, the goal is to predict and monitor pilot performance during landings effectively. Descent angle deviation was used as a criterion for evaluating landing performance as inadequate vertical position awareness during the approach phase was known to be a large contributor to inadequate situation awareness and approach-and-landing accidents [3]. Throughout this process, the paper will compare the advantages and disadvantages of two different computational approaches in handling the data.

Analysing remote flight data and pilot status data is essential to improve aviation performance, efficiency, and safety. Firstly, the analysis of remote flight data and pilot status data is critical for a high level of flight safety [4]. Continuous monitoring of aircraft parameters such as altitude, speed and system health, as well as monitoring of pilot status such as eye tracking, HRV, etc. helps in early detection of anomalies and timely intervention to reduce the likelihood of potential accidents and human error. Additionally, optimising flight operations and enhancing fuel efficiency are possible with the aid of remote flight data analysis. Airlines can find solutions to reduce emissions, optimise routes, and increase fuel efficiency by monitoring weather patterns, engine performance, and flight paths.

It is essential to approach flight safety monitoring from two angles to achieve successful monitoring: first, by monitoring and processing flight data; and second, by monitoring the pilot's condition [5]. Flight Data Monitoring (FDM) has evolved into an important tool for analysing aviation safety and performance. Continuous monitoring and analysis of FDM data provides a comprehensive view of an aircraft's dynamic behaviour, including pitch, roll and altitude angles. Most current flight data monitoring analyses are based on monitoring deviations from acceptable parameter ranges, such as low speeds for two pilots with dual flight control inputs [6]. Fewer studies have focussed on FDM in conjunction with external or physiological data to further speculate on flight data variations and assess pilot performance and actions. In this context, the introduction of eye tracking data can effectively complement the flight data, addressing the lack of pilot monitoring data [7]. Eye tracking on the flight deck has the potential to improve our understanding of pilot conduct and cognitive processes as the technology continues to advance [8].

Eye tracking techniques provide an objective measurement on understanding attention distribution and measuring pilot cognitive workload [9], [10]. Eye tracking allows for the non-intrusive, real-time monitoring of a pilot's gaze patterns, reaction speeds, and visual attention [11]. These measurements offer a special perspective on the mental strain that pilots experience during crucial stages like descent and landing. Pilot attentional patterns and reaction times to visual inputs can be used to measure workload, decision-making effectiveness, and situation awareness in general [8], [12], [13]. Studies using ocular features such as pupil diameter and blink frequency to assess cognitive

load have been conducted in many application areas [9]. Van et al. observed a strong linear relationship between the time derivative of pupil diameter and task performance measures [14]. Researchers found that in a numerical task in noise, the larger the pre-stimulus pupil diameter, the worse the task performance [15]. In addition, in studies with fixations, researchers have found that the distribution of fixations can effectively reflect the distribution of human attention and may affect the pilot's decision-making process [16]. All these indicate that it is possible to realise the quantitative analysis of pilot performance by supplementing flight data with eye-tracking parameters.

The selection of appropriate data analysis models is important for improving the accuracy and efficiency of data analysis and prediction. XGBoost is a powerful and widely used machine learning algorithm known for its efficiency and performance in various predictive modelling tasks [17]. It uses gradient boosting techniques to minimise the loss function by iteratively adding new models that focus on the errors of existing models. XGBoost is known for its scalability, speed, and ability to handle a wide range of data types and feature engineering techniques, making it a popular choice for regression and classification problems in machine learning [18]. XGBoost is not an artificial neural network, but a collection of decision trees. In addition, XGBoost is more efficient in dealing with large datasets and generates more accurate results because it uses decision trees to identify the most important variables and construct the model, whereas artificial neural networks can be computationally expensive and require more training time [19]. The general architecture of XGBoost is as follows:

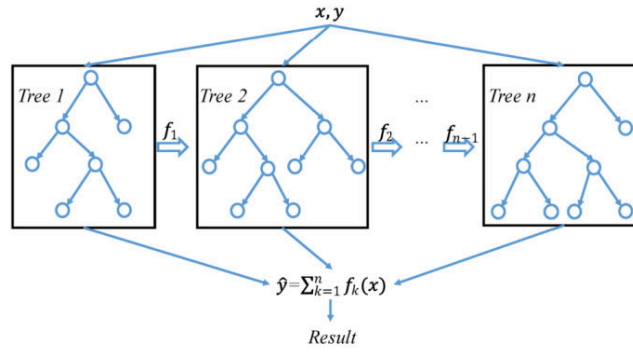


Fig. 1. The general architecture of XGBoost [20]

Transformer is a state-of-the-art architecture originally designed for natural language processing but has been adapted for time series forecasting [21]. In contrast to traditional Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), Transformer relies on a self-attention mechanism to capture long-range dependencies in the input sequence. This self-attention mechanism allows the model to dynamically attend to different parts of the input sequence and thus learn complex temporal patterns efficiently [22]. In terms of time series prediction, Transformer processes historical input sequences and directly predicts future values [23]. The general Transformer-based forecasting model is as follows.

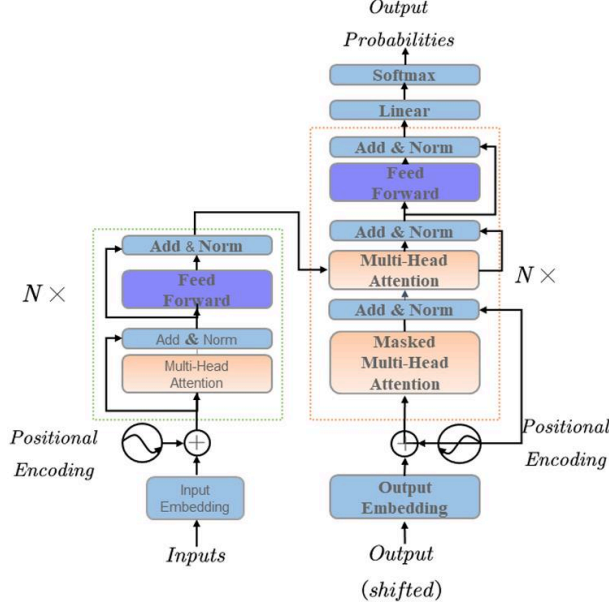


Fig. 2. The general architecture of Transformer forecasting model [24]

XGBoost excels in feature engineering, interpretability and scalability, while Transformer excels in capturing long-range dependencies, adaptation and end-to-end learning [25]. The choice between the two methods depends on the specific requirements of the forecasting task, the characteristics of the time series data, and the trade-offs needed between interpretability, performance, and computational efficiency.

2 Methodology

2.1 Participants

Twenty participants (15 males, 5 females) were invited to participate in this research. The participants had an average fixed-wing flying experience of 74.4 hours (mean = 74.4, *s.d.* = 93.9). In accordance with Cranfield University's Research Ethics System approval (CURES/14853/2021), data for this paper was collected from participants only for research purposes. Before the study began, a contract was given to each participant; only if they signed it could the experiment proceed, and they retained the right to terminate the trial at any time and have all of their data deleted. The participants' demographics are as follows:

Table 1. Participants' demographics

	Mean	SD
Age	32.15	10.70
Fix-wing flight hours	74.35	93.91
Simulator flight hours	64.5	221.60
Gender	15 male	5 female

2.2 Data collection and pre-processing

The Rolls-Royce Future System Simulator (FSS) at Cranfield University was used for this study. The FSS is a highly integrated future flight deck simulator with four big programmable touchscreens and two small side touchscreens. Using this simulator, researchers and pilots can investigate optimal procedures for a single-pilot operation flight deck with highly autonomous engines and novel technologies in the future [26].

Participants were asked to perform the landing task following the cues displayed to them by the Instrument Landing System (ILS) and precision approach path indicator (PAPI) while wearing the eye tracker (Fig. 2). The weather was clear, no turbulence. The starting point is at five miles final approach to the runway, at an altitude of 1400 feet and speed of 150 knots. The landing gear and throttle lever were all automated to maintain a constant approach speed. The simulator would automatically record all of the flight data, including flight path, altitude, and calibrated airspeed (CAS), which allowed to calculate the deviation from the desired route post-trial. Throughout the experiment, the environment was stabilized and well illuminated to increase the accuracy of the eye tracking data that was gathered.



Fig. 3. Participant performing the landing task in the FSS while wearing the eye tracker.

Data on eye-tracking were gathered for this study using the Pupil-Labs eye tracker. The components of this eye tracker include an eye camera that is fixed in a plastic frame to monitor eye characteristics and movement, and a world camera that synchronizes user viewpoints. The sample rate was 60 frames per second and the resolution was 1280 x 720 pixels. The eye camera would watch each participant's right eye in order to measure the pupil's diameter and gazes.

The altitude difference between the aircraft altitude and the reference altitude corresponding to the ideal 3-degree glide path was selected as a marker for evaluating the flight performance to be used as a target for prediction in this study. This variable is called ' ΔGP ' and determined is as follows:

$$GP = \tan(3) \times x_{thr} \times 6076.12 + CH_{thr}$$

$$\Delta GP = Altitude - GP$$

The parameters:

x_{thr} , representing the aircraft distance to the runway threshold in NM;

CH_{thr} , representing the crossing height, which is 50ft above the runway threshold height.

There were three factors used for GP prediction: Root mean square of deviation from the desired route (RMS), pupil diameter and the gaze position. Gaze is the basic unit of fixation, which contains not only the information of fixation, but also the information of saccade, which can fully reflect the participant's visual attention changes. And in 3D space, the gaze position is decomposed into three vectors under the XYZ axis. Then the data was cleaned to only keep the 4.5 NM to 1 NM to the runway threshold to exclude the possibility that the results varied too much due to large differences in the experience level of participants, affecting the accuracy of the predictions. Finally, the data were normalised: the data were scaled to a standard normal distribution with mean 0 and standard deviation 1:

$$X_{norm} = \frac{X - \mu}{\sigma}$$

2.3 Statistical tools used

The XGBoost regression prediction model and the Transformer time series prediction model used in this study are two of the more representative approaches in machine learning and Artificial Neural Networks (ANN).

The XGBoost is an ensemble machine learning technique based on trees that generates several decision trees (a weak learner) and merges them into a prediction model (a strong learner). In each iteration, it develops a new tree greedily in order to lower the residuals of the previous model. This technique is a type of gradient-boosted tree approach. The 'Sklearn' package was used in the Python for the XGBoost algorithm.

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f_k \in F \quad (1)$$

In the formulas, the f_k is a function of an independent tree with the specific tree structure and leaf weight. K represents the total number of additive functions. The space of the classification and regression trees (CART) is represented by F . At the t -th iteration, the objective function $\mathcal{L}^{(t)}$ that has to be optimized can be written as follows:

$$\mathcal{L}^{(t)} = \sum_{i=1}^n \ell(y_i, \hat{y}_i) + \Omega(f_t) \quad (2)$$

In the formulas, ℓ is the loss function that measures the truth y_i and the prediction $\hat{y}_i$. The regularisation term, $\Omega(f_t)$, penalizes the model's complexity to prevent overfitting.

$$\Omega(f_t) = \gamma T + \frac{1}{2} \lambda ||\omega||^2 \quad (3)$$

The basic principle of Transformer's time series prediction is to convert the time series data into a sequence format, then capture the correlation between different positions in the sequence through a self-attention mechanism, and finally make the prediction through a multilayer feedforward neural network based on positional encoding. In this research, the 'PyTorch' package was used for the Transformer algorithm in Python. By debugging the Transformer model, the optimiser was set to RMSprop, which adaptively adjusts the learning rate for each parameter, thus avoiding the problem of learning rates decaying too quickly. The learning rate was initially set to 0.0001 and the epochs was set to 25. The Self-Attention formulas is as follows:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (4)$$

In the formulas, the Query (Q) is the vector used to calculate the attention score. The Key (K) is the vector that measures the similarity between Query and Value. The Value (V) is the vector used to calculate the weighted average value.

3 Results & Discussion

3.1 Comparing for two forecasts methods

The transformer time series forecasting model and the XGBoost forecasting model were used to predict the ' ΔGP ' representing the flight performance in this research. The gaze position in X axis (gaze_x), gaze position in Y axis (gaze_y), gaze position in Z axis (gaze_z), RMS and pupil diameter. The accuracy of the predictions using the two methods is shown in the table below. It is clear to notice that the results for both MAE (mean absolute error) and RMSE values were smaller when using the XGBoost method, meaning that the accuracy of the prediction was higher. And with the higher prediction accuracy of XGBoost, it has advantages that Transformer does not have: fast computation and lower equipment requirements. The length of the computation using Transformer is much longer than that of XGBoost, which is a high requirement for the hardware. The convergence of the Transformer model is difficult due to the large discrete

values of the eye tracking data and is subject to large individual differences in participants.

Table 2. Participants' performance against XGBoost and Transformer values

	XGBoost	Transformer
RMSE	42.29	102.10
MAE	25.18	78.01

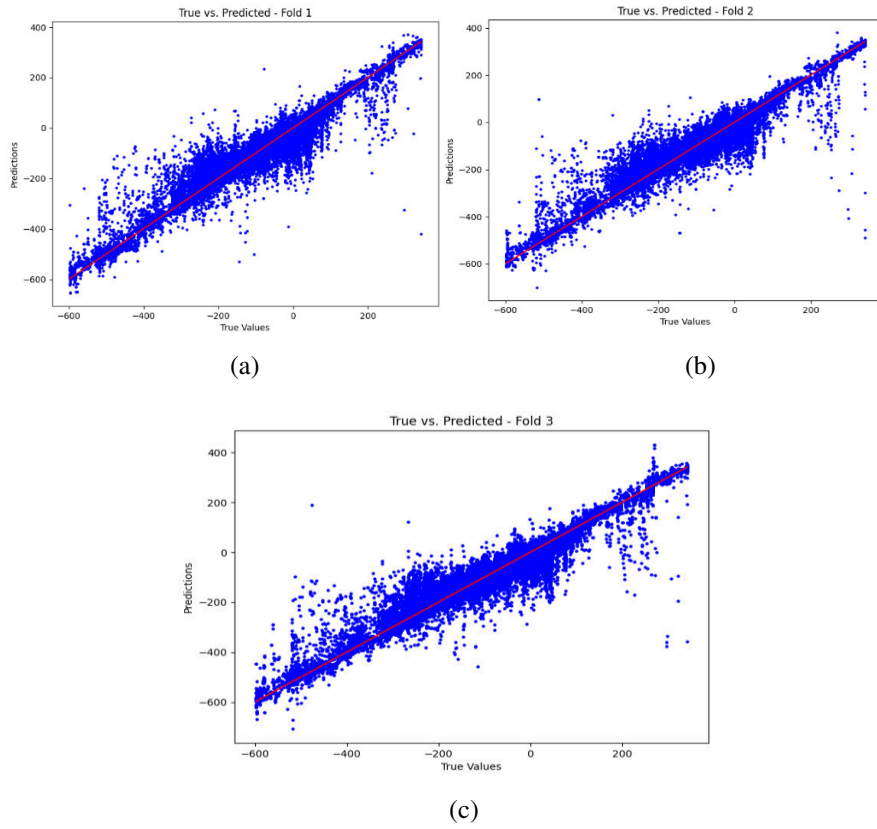


Fig. 4. The true-predicted value scatter plot in XGBoost model. X-axis is the true value and Y-axis is the predicted value. Subfigures (a), (b) and (c) represent the results for each fold in a 3-fold validation set.

The true-predicted value scatter plot for prediction using the XGBoost model is shown in Figure 4. It can be found that the scatter points are approximately arranged on a diagonal line, indicating a high prediction accuracy. However, it is worth noting that the lower prediction accuracy was found near the extremes in all three folds. Firstly,

it may be because these extremes are outliers that are not suitable for prediction. Secondly, these extremes may represent unacceptable deviations (e.g., due to the skill level of the pilots), which affects the accuracy of the prediction.

Based on the comparison between the models built by XGBoost and Transformer, it is observed that XGBoost achieves higher predictive accuracy. This finding suggests several possible reasons. Firstly, XGBoost is a highly optimized ensemble learning algorithm specifically designed for tabular data, which may be more suitable for the particular characteristics of this dataset. Secondly, XGBoost relies on decision trees, which are capable of capturing complex nonlinear relationships in the data, while Transformer may struggle to model certain types of tabular data effectively. Additionally, XGBoost typically requires less data preprocessing and tuning compared to Transformer, which can simplify the modelling process and reduce the risk of overfitting. Therefore, further investigation and experimentation are warranted to better understand the factors influencing the relative performance of XGBoost and Transformer in different scenarios.

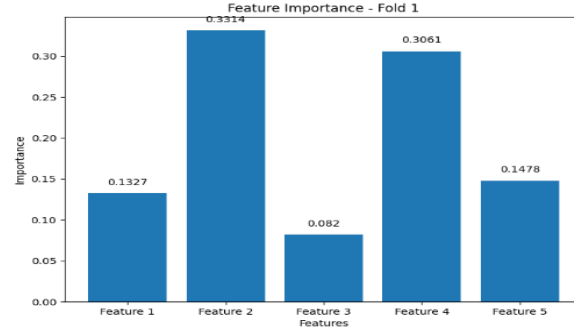
3.2 Features importance analysis in XGBoost model.

The importance of different features in forecasting model building is analysed using 3-fold cross-validation. The features are gaze_x (feature 1), gaze_y (feature 2), gaze_z (feature 3), RMS (feature 4) and pupil diameter (feature 5). The importance for the models are shown as follows:

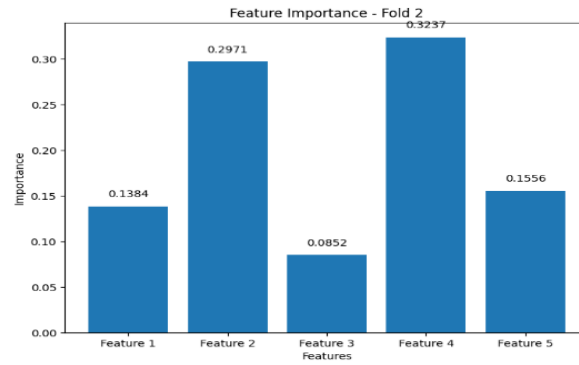
The gaze_y (feature 2) had a significantly high importance in model (weight_1 = 0.3314, weight_2 = 0.2971, weight_3 = 0.3132), indicating that changes in gaze position in the vertical direction are strongly weighted for analysing flight performance during descent. Changes in gaze position in the vertical direction may indicate that the pilot frequently switches attention between the display and out the window, which affects the pilot's performance during landing [27].

The RMS (feature 4) also had a high importance in predicting ΔGP (weight_1 = 0.3061, weight_2 = 0.3237, weight_3 = 0.3125). The RMS deviation to the desired route reflects the accuracy of the piloting actions during descent and it is highly related to the altitude changes, thus, it occupies a higher weight in the prediction of the ΔGP .

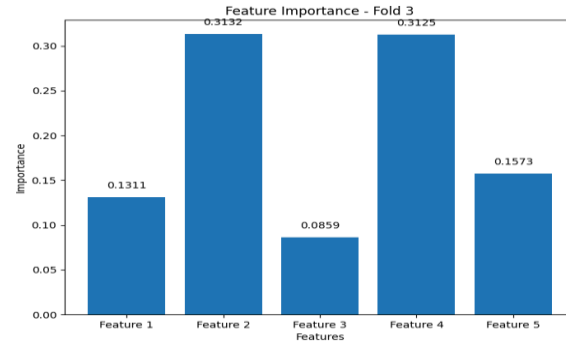
Gaze_x (feature 1) and pupil diameter (feature 5) possess similar importance in analysing ΔGP . The correlation between gaze position and performance during landing is mainly due to the pilot's lateral shift of attention between the primary flight display and the navigation display, so the acquired landing-related information may affect the pilot's situation awareness and thus the landing performance. Whilst this lateral shift of attention may be influenced by external factors such as cockpit instrumentation layout, the feature of pupil diameter correlates with the pilot's tension level and workload level, which may affect the flight performance during landing [28].



(a)



(b)



(c)

Fig. 5. Feature importance for the XGBoost model. Subfigures (a), (b) and (c) represent the results for each fold in a 3-fold validation set.

3.3 Limitations

As an exploratory study, this study had the following limitations. Firstly, the sample size was small and not fully representative of all pilots. Data from only 20 participants were retained for analysis due to eye-tracking data accuracy issues. Secondly, although the accuracy of the model was acceptable overall, the extreme ends suffered from lower prediction accuracy which may have been due to the pilots' performance. The homogenisation of the models used results in the Transformer model did not achieve the desired accuracy and does not represent its capability in time series prediction of flight performance. Finally, for future studies, a more diverse selection of parameters may help to better represent the flight data and pilot physiological data, which may enhance the predictive potential for pilot performance.

4 Conclusion

Achieving the monitoring and prediction of pilot performance is important for improving flight safety and realising future remote flight safety monitoring. In order to investigate the analysis and prediction of pilot performance, this study analyses the prediction outcomes of two distinct time-series forecasting models, XGBoost and Transformer, using two types of data: flight data and pilot physiological data. The gaze (decomposed into three vectors under the XYZ axis), pupil diameter and the RMS of deviation to desired route were selected to predict the pilot performance indicator: ΔGP , the altitude difference between the aircraft altitude and the reference altitude corresponding to the ideal 3-degree glide path. The results show that the simpler structure of XGBoost has a higher prediction accuracy, and the calculation process is simpler and faster. Factor significance analyses showed that gaze's component on the z-axis and RMS had a more significant effect on predicting ΔGP . On the contrary, this does not mean that neural network algorithms, represented by Transformer, do not have the potential for flight performance analysis and prediction. The parameters selected in this study were small, but with the use of a larger number of parameters (big data) and an increase in the computing power of the computing device, Transformer may have better performance. This study provides an exploration for future analysis and prediction of flight performance by combining flight data with pilot physiological data or other parameters. Future research could consider adding different parameters and selections to improve the algorithm to further enhance the accuracy of the prediction.

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