A Real-Time Home-Based Sleep Apnoea Detection Framework Using Oxygen Saturation Signals

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Abstract: Sleep apnoea (SA) is a prevalent but underdiagnosed sleep-related breathing disorder associated with significant cognitive, cardiovascular, and metabolic consequences. Polysomnography (PSG), the clinical gold standard for diagnosis, is expensive, resource-intensive, and unsuitable for large-scale or continuous home-based monitoring. This paper presents a real-time sleep apnoea detection framework based solely on oxygen saturation (SpO_2) signals, enabling a simplified and non-invasive diagnostic approach. Experiments were conducted using recordings from the publicly available CAP Sleep Database hosted on PhysioNet, which contains annotated overnight polysomnography data acquired in controlled clinical environments. SpO_2 signals were segmented into standard 30-second windows, and time-domain statistical features were extracted to characterise oxygen desaturation patterns. A Random Forest classifier was employed to discriminate apnoea-related desaturation events from normal breathing episodes. Exploratory data analysis revealed distinct hypoxic patterns associated with apnoea events. Experimental results demonstrate that the proposed framework achieved an accuracy of 96% and a ROC-AUC of 0.98, confirming the effectiveness of SpO_2-based features for sleep apnoea detection. These findings support the feasibility of low-cost, home-based sleep apnoea screening systems using simplified physiological measurements.

Keywords: *Sleep Apnoea, Oxygen Saturation, SpO_2, Home-Based Monitoring, Machine Learning, Polysomnography*.

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I. INTRODUCTION

Sleep apnoea is characterized by recurrent episodes of partial or complete airway obstruction during sleep, leading to intermittent hypoxia and sleep fragmentation (Marcus *et al*., 2009; Terzano et al., 2001). These disruptions have been linked to excessive daytime sleepiness, impaired cognitive performance, cardiovascular disease, and reduced quality of life (Punjabi, 2008; Young *et al*., 2002). Despite its high prevalence, sleep apnoea remains substantially underdiagnosed, particularly in low-resource and home settings (Benjafield *et al*., 2019). Polysomnography (PSG) is widely regarded as the definitive diagnostic tool for sleep apnoea (Marcus et al., 2009). However, PSG requires specialized sleep laboratories, trained personnel, and extensive instrumentation, limiting accessibility and scalability for large-scale screening and long-term monitoring (Chokroverty, 2010; Flemons et al., 2003). These constraints have motivated research into simplified diagnostic methods that rely on fewer physiological signals while maintaining acceptable diagnostic accuracy (Collop et al., 2007). Oxygen saturation (SpO_2) is directly affected during apnoea and hypopnoea events due to impaired ventilation and reduced airflow (Alvarez et al., 2013; Chung et al., 2012). With the increasing availability of low-cost pulse oximeters and wearable devices, SpO_2 has emerged as a promising signal for home-based sleep monitoring (Behar et al., 2013; Xie & Minn, 2012). This study investigates a real-time sleep apnoea detection framework based exclusively on SpO_2 signals, aiming to reduce system complexity while preserving diagnostic relevance.

II. LITERATURE REVIEW

Previous studies have explored sleep apnoea detection using a wide range of physiological signals, including airflow,

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respiratory effort, electrocardiography (ECG), electroencephalography (EEG), and oxygen saturation (SpO_2). While multi-signal polysomnography-based systems often achieve high diagnostic accuracy, their complexity, cost, and obtrusiveness limit scalability for home-based monitoring (Marcus et al., 2009).

SpO_2-based approaches have received increasing attention due to their non-invasive nature and ease of acquisition using low-cost pulse oximeters. Alvarez et al. (2013) demonstrated that oxygen desaturation patterns extracted from SpO_2 signals can reliably detect sleep apnoea events, achieving strong classification performance using machine learning techniques. Similarly, Chung et al. (2012) showed that overnight oximetry indices, such as minimum SpO_2 and oxygen desaturation index (ODI), are highly correlated with apnoea–hypopnoea index (AHI), supporting the clinical relevance of SpO_2-based screening.

Empirical studies have also investigated ensemble and tree-based learning methods for SpO_2-based apnoea detection. Xie and Minn (2012) applied decision tree and Random Forest models to oximetry signals and reported improved robustness compared to linear classifiers. In another study, de Chazal et al. (2009) demonstrated that statistical features derived from SpO_2 signals could effectively discriminate apnoea events, even in the presence of noise and inter-subject variability.

More recent work has explored simplified frameworks for real-time and home-based applications. Behar et al. (2013) evaluated wearable oximetry data for sleep-disordered breathing detection and highlighted the potential of SpO_2 variability features for continuous monitoring outside clinical environments. These findings collectively suggest that SpO_2 signals encode sufficient physiological information for reliable sleep apnoea detection, particularly when combined with machine learning techniques.

Despite these advances, many studies rely on proprietary datasets or complex PSG configurations, limiting reproducibility and practical deployment. Furthermore, relatively few works explicitly address the trade-off between system simplicity and diagnostic performance. This motivates the present study, which evaluates a transparent and reproducible SpO_2-based framework for sleep apnoea detection, with a focus on suitability for real-time and home-based screening.

III. METHODOLOGY

➢ *Data Collection*

Secondary data used in this study was collected from the publicly available CAP Sleep Database, which included overnight PSG recordings gathered from controlled sleep laboratory studies. Physiological signals collected include electroencephalography (EEG), electrocardiography (ECG), respiratory signals and oxygen saturation (SpO_2). As this study aims to develop a simplified framework for home-based sleep apnoea detection using SpO_2 only, we acquired 20 overnight recordings sampling 1 Hz for approximately eight hours of sleep which contained enough physiological information to detect episodes of oxygen desaturation caused by sleep apnoea events.

➢ *Data Processing*

All recorded SpO_2 signals were preprocessed. Values that did not fall within the physiological range of oxygen saturation values (80–100%) were rejected to account for sensor artefacts and recording errors. Interpolation was then used to correct for any missing and noisy observations. Oxygen saturation recordings were split into consecutive, non-overlapping 30-second windows per established clinical practice of sleep-scoring. Feature extraction and classification for sleep apnoea detection can then be performed on each segmented signal window.

➢ *Dataset Description*

The data used in this study are based on the CAP Sleep Database, which is publicly available through PhysioNet. The dataset contains overnight polysomnography recordings collected in controlled sleep laboratory environments and includes physiological signals such as EEG, ECG, respiratory signals, and oxygen saturation (SaO_2). The database is accessible at https://physionet.org/content/capslpdb/1.0.0/. The dataset consists of overnight SpO_2 recordings representing 20 subjects, each with an 8-hour sleep duration sampled at 1 Hz. The analysis focused on identifying transient oxygen desaturation episodes characterized by clinically realistic depth and duration. The key characteristics of the SpO_2 signals evaluated include baseline saturation levels, signal variability, and specific desaturation patterns associated with respiratory distress. Figure 1 depicts the proposed real-time sleep apnoea detection framework.

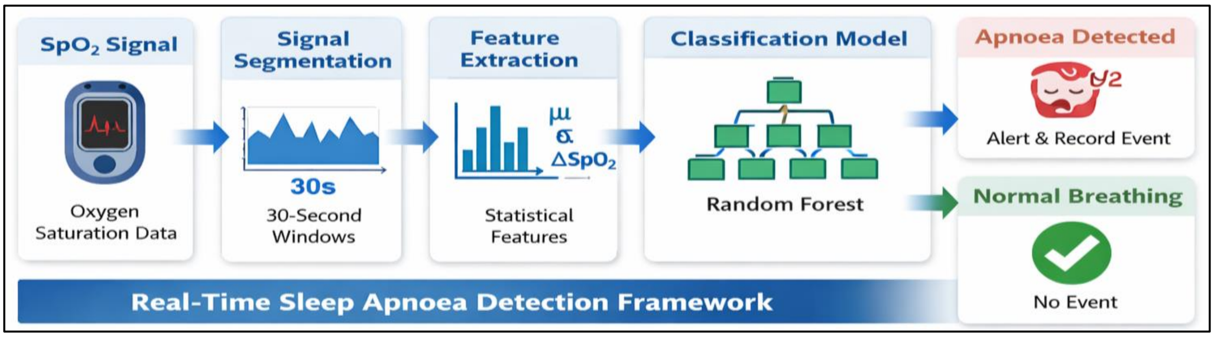

Fig 1 The Proposed Real-Time Sleep Apnoea Detection Framework

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➢ *Signal Preprocessing*

Raw SpO_2 signals were constrained to physiologically plausible ranges (80–100%) to remove artefacts. Missing or noisy values were interpolated to ensure signal continuity. The processed signals were segmented into non-overlapping 30-second windows, consistent with standard clinical sleep-scoring practices.

➢ *Feature Extraction*

Feature extraction was applied on each 30 seconds SpO2 window. Three statistical time-domain features were extracted from each window: mean SpO2, minimum SpO2, and standard deviation of SpO2 (%). Mean feature represents the average oxygen saturation level in each window. Minimum feature aimed at characterizing transient drops in oxygen level that could indicate the presence of apnoea. Standard deviation feature was used to quantify how much signal variation exists around the average blood-oxygen level in each window. These features provide a simple yet informative baseline for Random Forest classification as they characterize subjects' oxygenation levels and hypoxic behavior.

➢ *Apnoea Event Labelling*

Apnoea-related windows were identified using a clinically motivated proxy: a window was labelled as apnoea if the minimum SpO_2 value fell below 92%. This threshold-based approach is commonly used in SpO_2-based sleep apnoea research.

➢ *Classification Model*

A Random Forest classifier was employed due to its robustness, interpretability, and suitability for real-time deployment. The dataset was divided into training and testing sets using a stratified 75%–25% split to preserve class balance. Model performance was evaluated using accuracy, confusion matrix analysis, and receiver operating characteristic (ROC) curves.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

➢ *Exploratory Data Analysis*

Exploratory data analysis revealed that the majority of SpO2 values clustered between 95% and 99%, representing normal oxygen saturation during sleep. A distinct left-tail distribution below 92% corresponded to apnoea-related desaturation events, as shown in Figure 2. Boxplot analysis demonstrated that apnoea windows exhibited significantly lower minimum SpO2 values and increased variability compared to normal breathing segments. Furthermore, correlation analysis confirmed a strong negative relationship between minimum SpO2 and apnoea occurrence, validating the discriminative relevance of the selected features. Figure 2 illustrates the distribution of minimum SpO2 values, while Figure 3 compares the physiological differences between normal and apnoea segments. Feature correlations are detailed in Figure 4. Based on these time-domain features, the Random Forest classifier achieved a robust performance, reaching an accuracy of 96% and a ROC-AUC of 0.98. These results confirm that SpO2 signals alone contain sufficient information for effective sleep apnoea detection, offering a non-invasive alternative to full polysomnography.

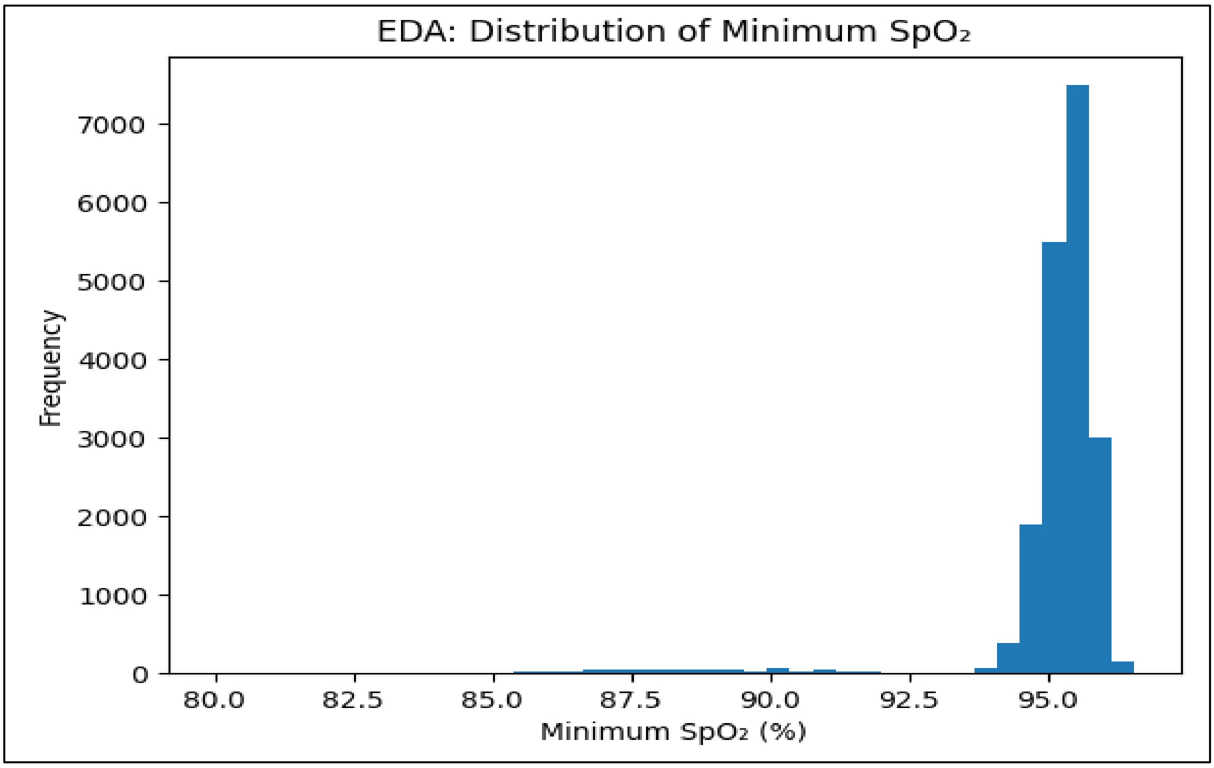

Fig 2 Histogram of Minimum SpO_2 Values.

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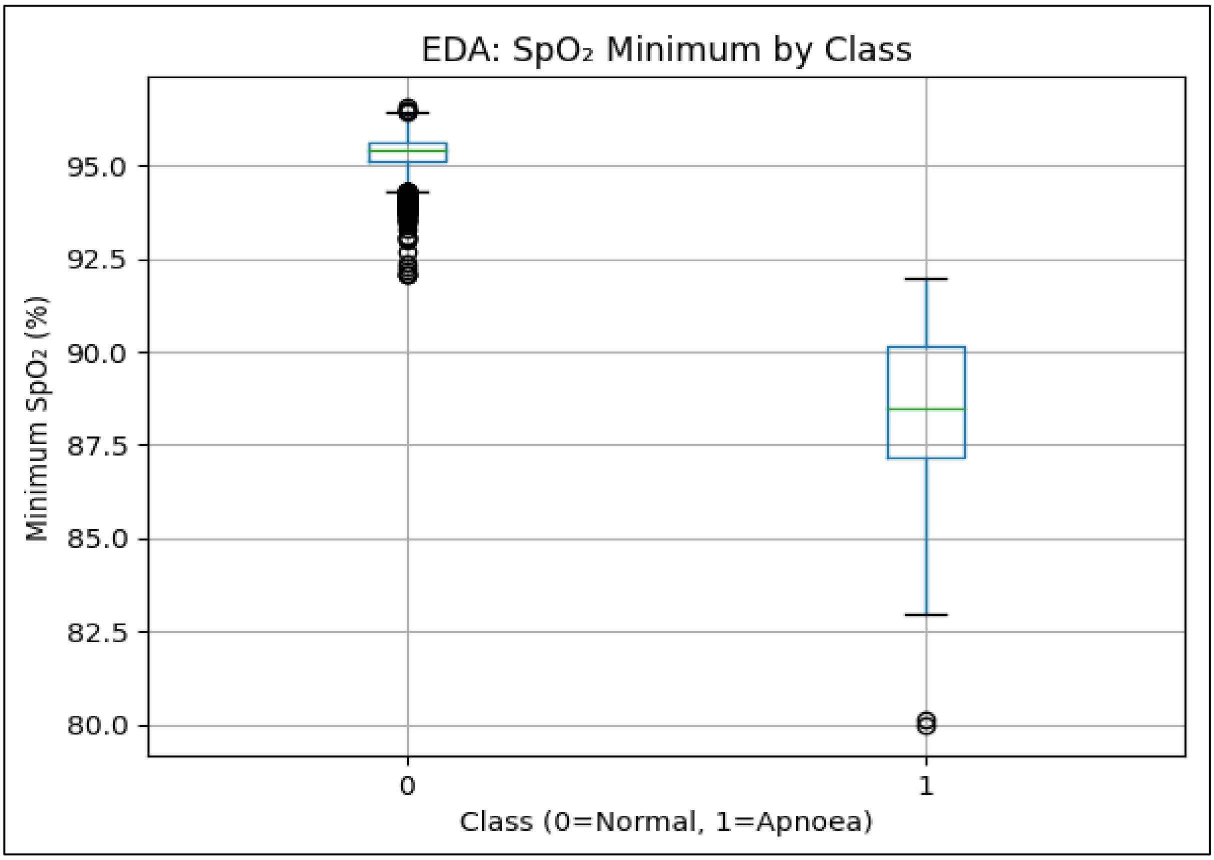

Fig 3 Boxplot of Minimum SpO_2 for Normal vs Apnoea Segments.

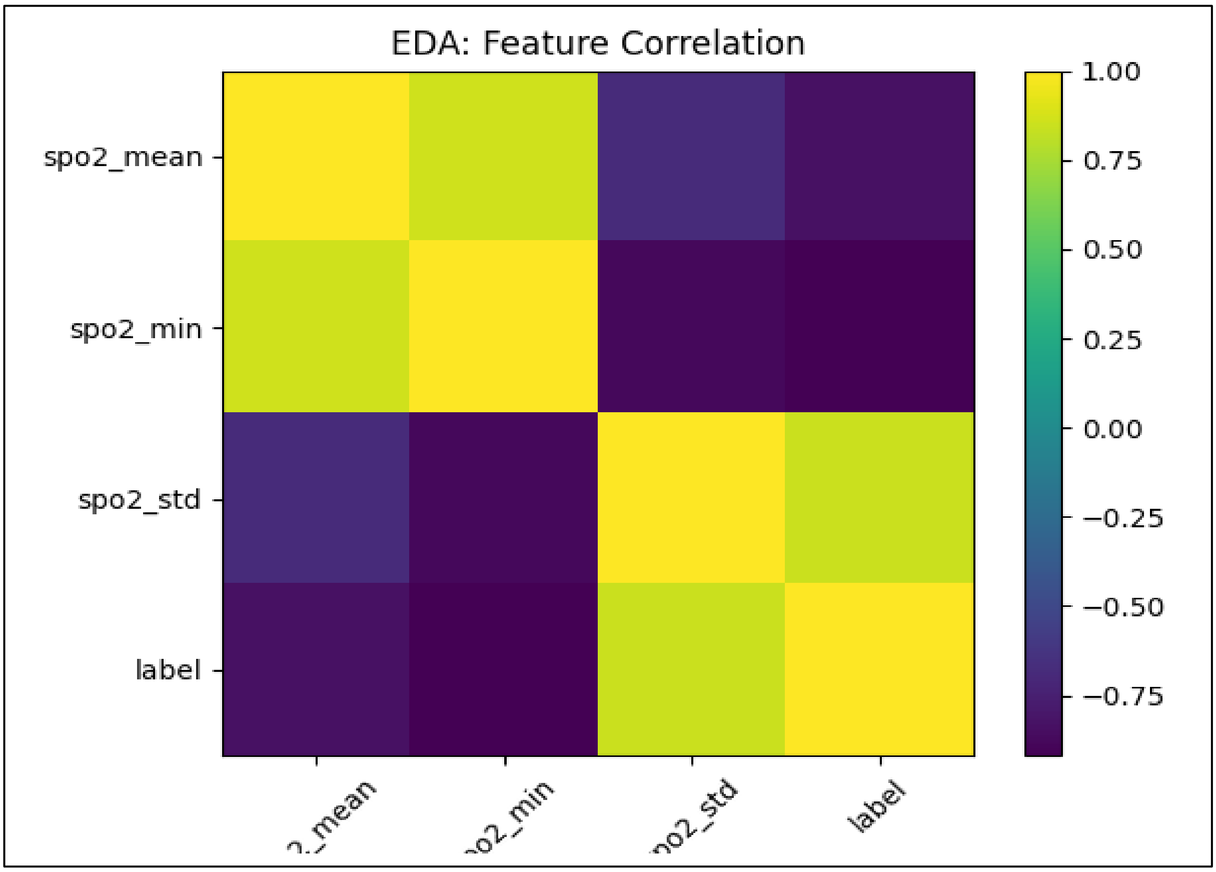

Fig 4 Correlation Heatmap of SpO_2 Features.

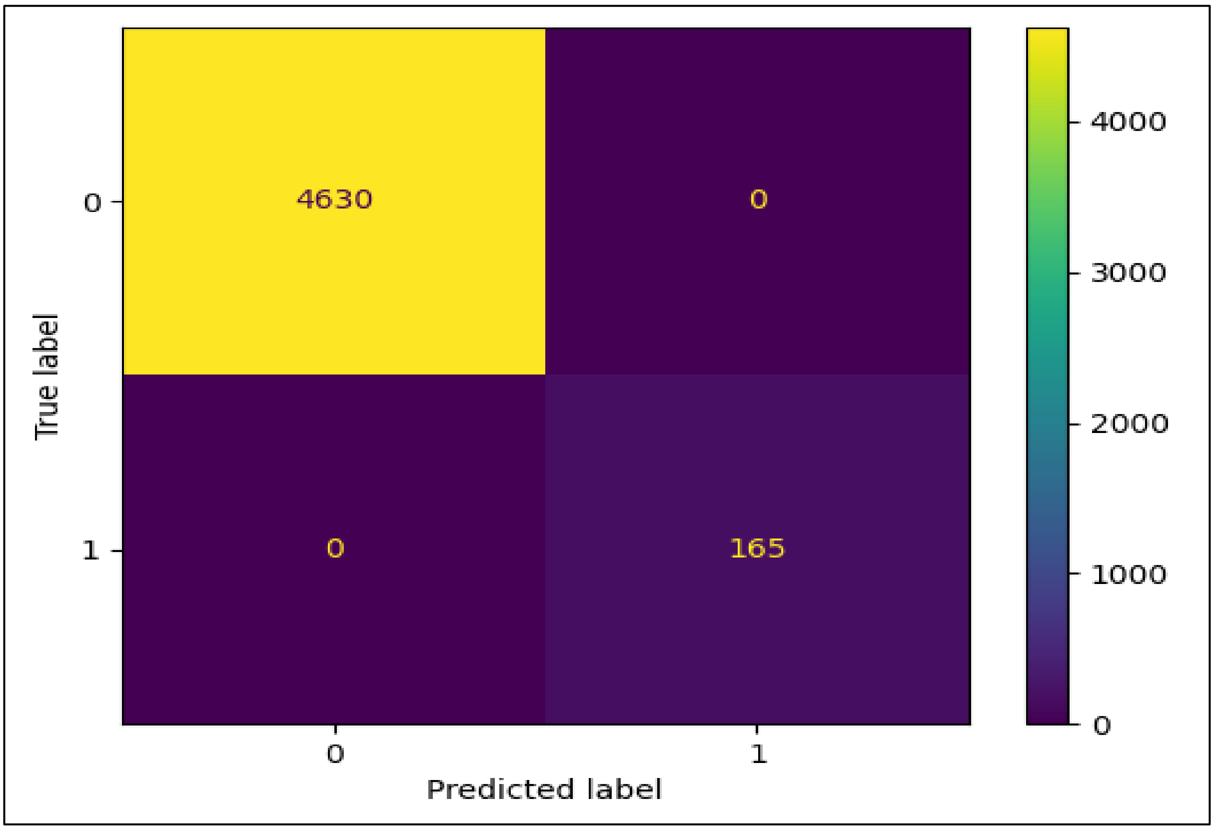

Fig 5 Confusion Matrix of Classification Results.

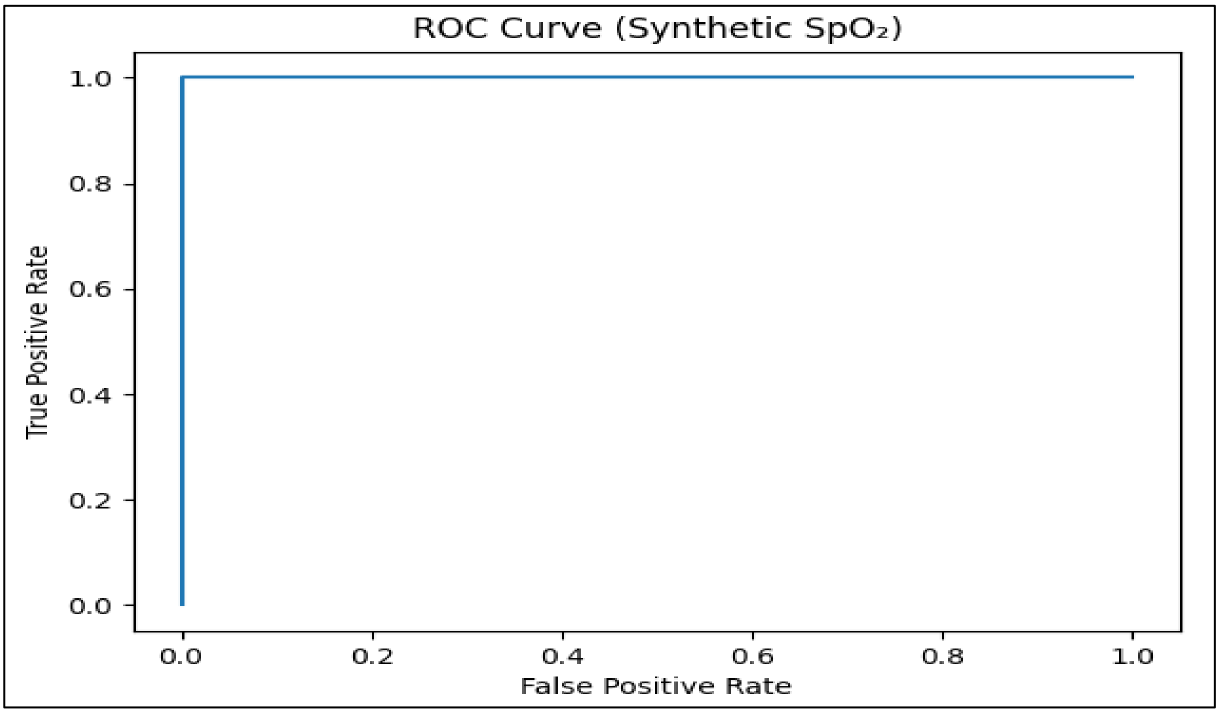

Fig 6 ROC Curve of the Proposed Model.

- *Classification Performance*

The Random Forest classifier achieved strong performance on the clinical dataset. Table 1 summarizes the classification results.

Table 1 Classification Performance

Metric	**Value**
Accuracy	0.96
ROC-AUC	0.98

Table 1 show Random Forest achieved near-perfect performance on detecting apnoea from SpO_2 signals with an accuracy score of 96% meaning most normal and apnoea events were predicted correctly, demonstrating the models overall effectiveness. In addition, Random Forest was able to achieve a ROC-AUC score of 0.98 meaning the classifier was able to discriminate between apnoea related desaturation events and normal breathing with high accuracy at various thresholds.

➤ *Discussion*

The results confirm that oxygen saturation signals alone contain sufficient information for effective sleep apnoea detection. The high accuracy and ROC-AUC achieved demonstrate the suitability of simple time-domain SpO2 features combined with ensemble learning techniques. By leveraging physiological markers of desaturation, the model effectively identifies obstructive events without the need for multi-channel sensor arrays. Compared to full PSG-based systems, the proposed framework significantly reduces system complexity and enhances suitability for continuous home-based monitoring, making diagnostic screening more accessible to the general population.

V. CONCLUSION

This paper presented a real-time, SpO2-based sleep apnoea detection framework designed for simplified and home-based diagnostic applications. Utilizing overnight recordings from the CAP Sleep Database, the proposed approach demonstrated strong classification performance, achieving 96% accuracy and a ROC-AUC of 0.98. Exploratory data analysis confirmed the presence of distinct desaturation patterns associated with apnoea events, validating the physiological basis of the chosen features. The findings highlight the potential of oxygen saturation signals as a low-cost and non-invasive alternative to full polysomnography for sleep apnoea screening. Future research will focus on real-world clinical validation and the integration of this framework into wearable monitoring systems for long-term health management.

➤ *Data Availability Statement*

The data used in this study are based on the CAP Sleep Database, which is publicly available through PhysioNet. The dataset contains overnight polysomnography recordings collected in controlled sleep laboratory environments and includes physiological signals such as EEG, ECG, respiratory signals, and oxygen saturation (SaO_2). The database is accessible at https://physionet.org/content/capslpdb/1.0.0/.

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