FUZZY LOGIC-ENHANCED DEEP NEURAL NETWORKS FOR SLEEP APNEA SEVERITY CLASSIFICATION THROUGH SNORING DETECTION

by

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DEDICATION

Esta tesis va dedicada a mis padres Sylvia y Alejandro que siempre me han dado las herramientas y la confianza para perseguir y conseguir los objetivos que me proponga. Gracias por abrirme las puertas y estar al tanto de cualquier problema que pueda tener. Quiero agradecer a Martha por darme siempre la fuerza y el apoyo de seguir dando lo mejor de mí siempre que me encontraba dudando de mis capacidades y por siempre darme compañía cuando más lo necesitaba. Fuiste mi piedra durante estos dos años y estoy muy agradecido de haberte tenido en mi esquina.

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This research investigates the underestimated health implications of obstructive sleep apnea (OSA), a common condition affecting nearly 30 million individuals in the United States leading to significant health complications. The primary focus is on evaluating the severity of key symptoms through the development of a convolutional neural network (CNN). A CNN is trained to distinguish between snoring and non-snoring episodes providing a basis for calculating the snoring index, which quantifies the number of consecutive snoring episodes within an hour. Research has shown that both frequency and intensity of snoring can be correlated to the severity of sleep apnea.

Complementing this analysis an oxygen saturation device connected to a raspberry pi is incorporated to measure blood oxygen levels (Spo2) and additional metric for assessing apneas and hypopneas. The combination of these three variables, snoring index, intensity and Spo2 form a basis for an approximate evaluation of the severity of sleep apnea symptoms. To achieve this, a fuzzy inference system is employed to categorize the severity of the symptoms into distinct levels: normal, mild, moderate, severe, and critical.

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CHAPTER ONE: INTRODUCTION

Sleep apnea, a prevalent sleeping disorder affecting nearly 30 million adults in the United States, involves the recurrent complete or partial obstruction of the upper airway during sleep. This obstruction leads to periodic episodes of reduced airflow, disrupting the normal breathing rhythm [1,2]. Events of apnea coincide with a reduction of oxygen saturation that triggers a chain of responses in the body and poses serious health consequences such as heart failure [3]; nonetheless, 80% of the sufferers remain undiagnosed [4]. Given the fatal casualties that this represents, a method to detect and classify the severity of sleep apnea at a cost-efficient and convenient for affected individuals is of utmost importance. While polysomnography (PSG) tests remain the gold standard in diagnosing OSAS, their methodology requires a comprehensive overnight recording of various parameters such as brain waves, oxygen levels, heart rate, and respiratory patterns during sleep [5]. Despite the efficiency in diagnosis, PSG comes with specific challenges. It is a resource-intensive process that requires expensive technical equipment and expert technicians, making it expensive and inconvenient for patients.

OSAS severity is classified by the apnea-hypopnea index (AHI), which measures the average of apneas and hypopneas that a patient experiences per hour during sleep.
An *apnea* defines the partial or complete obstruction of breeding during sleep for a duration exceeding 10 seconds. Depending on the episodes, the severity ranges from mild to moderate to severe. A mild obstruction is categorized between 5 and 15, while a moderate obstruction is categorized in the ranges of 15 and 30. Anything above 30 is considered a severe obstruction. Noticeable symptoms of OSA include loud and frequent snoring interrupted by periods of quiet and resumed by a loud sound once breathing resumes [6, 7]. These quantifiable criteria could serve as pivotal indicators in acknowledging the severity of OSAS symptoms, which often go

unnoticed. The development of tools capable of classifying severity could help manage and mitigate the risks associated with these symptoms, which are observable in everyday life and hold significant promise. Creating user-friendly methods for evaluating these indicators can enhance the diagnosis of OSAS, bring awareness to the current state of mild and heavy snorers, and facilitate more appropriate treatment strategies.

CHAPTER TWO: LITERATURE REVIEW

Deep learning models, particularly CNNs and deep recurrent networks based on Long Short-Term Memory (LSTM), have been widely used in applications of sound event detection. These models demonstrated effectiveness in capturing essential features of sound by processing input features from the time-frequency domain, achieved through the transformation of audio signals using a Short-Time Fourier Transform (STFT). Features such as Mel spectrograms, Mel-Frequency Cepstral Coefficients (MFCCs), and chroma features enable these deep learning models to find the features that differentiate sounds and speech [9,10,11].

Khan [12] achieved a notable 96% accuracy in detecting snoring using a deep CNN with MFCC features and incorporated the model into a smart wearable gadget that sent back a vibration. Arsenali [13] similarly achieved promising results but did so with RNN, using MFCC as the primary audio feature. A combination of both CNN and RNN was employed by Xie [14], utilizing a spectrogram to feed the CNN and forward the flattened layer of the CNN to the RNN to add sequential memory. At the same time, these works proved to be very promising in the advancements of snoring sound classification. It is noteworthy their limitation in directly addressing sleep apnea.

Although snoring is prevalent in up to 94% of OSAS patients, its standalone presence is insufficient to provide conclusive metrics for a diagnosis, regardless of its high correlation to the disorder, as not all snoring can be categorized as OSAS [8]. Recognizing this limitation emphasizes the importance of a multi-characteristic diagnostic approach that considers multiple factors. However, snoring detection remains an essential aspect of the severity of sleep apnea. Relevant work has arisen in applying deep learning models for sleep apnea classification; Kang [15] contributed to the field by developing a hybrid neural network to classify events such as snoring, apnea, and silence, achieving results over 85%. While this work successfully distinguishes apneic sounds from snoring. Taking this contribution forward, Luo [16] uses a Temporal CNN (TCNN) and applies the apnea classification in real time. There remains a need to assess the severity of such events. In line with this, our research seeks to extend the existing knowledge by focusing on classifying the potential severity of snoring events and determining appropriate action.

The correlation between snoring and sleep apnea severity has been investigated by Su Geun [17], who introduced a snoring index defined as three consecutive snoring episodes no more than 10 seconds apart. Su Geun’s research revealed that the frequency of consecutive snoring episodes, or the snoring index per hour, directly correlated to the severity of OSA. In alignment with this research, we aim to employ CNN to classify snoring events in real time and track a counter of consecutive snoring episodes. This counter will contribute to calculating a snoring index, providing the first feature that can indicate the severity of sleep apnea. Our approach seeks to assess OSAS severity based on snoring patterns by leveraging real-time classification and continuous overnight monitoring.

Snoring intensity is an additional feature often sought to indicate OSAS and its severity. Noisy sleep is a common feature of possible airway obstruction; the more potent the snore, the greater the chances of an apnea [18]. According to Maimon [19], the belief that louder snores are associated with riskier OSA conditions is substantiated by their analysis of 1643 snorers distributed among four categories of OSA severity. Their findings demonstrated a positive correlation between snoring intensity and the increase in the AHI. We have selected intensity as our second feature in assessing severity. As our CNN model detects snoring, it will extract the audio's intensity concurrently, maintaining an average decibel level during continuing snoring events.

Sharma [20] proposed a promising advancement in applying deep neural networks for sleep apnea detection. In contrast to other studies in the field, Sharma's approach involves a 1D CNN that directly processes 30 seconds of pulse oximeter recordings of vitals for binary classification of apnea or no apnea episodes. Taking raw data without needing to preprocess for hand-crafted features is an advantage to real-world applications as it requires low latency to perform inferences. The results seem promising in detecting OSA and different types of apnea, such as Central sleep apnea (CSA) and Mixed sleep apnea (MSA). The proposed method demonstrated significant results confirming the importance of SpO2 and heart rate in diagnosing OSAS. The correlation between SpO2 and the severity of AHI is explored by Wali [21], who sought to evaluate different parameters related to oxygen saturation to identify correlations with AHI. His finding concluded that various parameters in oxygen saturation correlate with the Apnea-Hypopnea Index. However, Wali also states how the best way of defining OSA severity remains unclear.

Given the ambiguity in classifying OSA severity, we introduce a fuzzy inference system to process fuzzy values of parameters that correlate with OSAS severity. This system outputs a crisp value representing the severity of the symptoms, providing an exciting and flexible approach to classification.

As stated before, the core objective of our study is to assess the severity cost-efficiently and user-friendly. Our proposed method involves a CNN for detecting snoring events. For each snoring event, a timestamp is generated to calculate the time until a subsequent snoring event occurs. If the time is under 10 seconds, the event is considered consecutive and contributes to the snoring index counter, the first input for our fuzzy system. The two other inputs consist of the average snoring intensity for a given time window and the minimum oxygen saturation obtained from a pulse oximetry sensor. These inputs are fed into the fuzzy inference system, which determines the severity based on rules developed through research. This comprehensive approach aims to provide a practical and effective evaluation of sleep apnea severity. (Fig. 1)

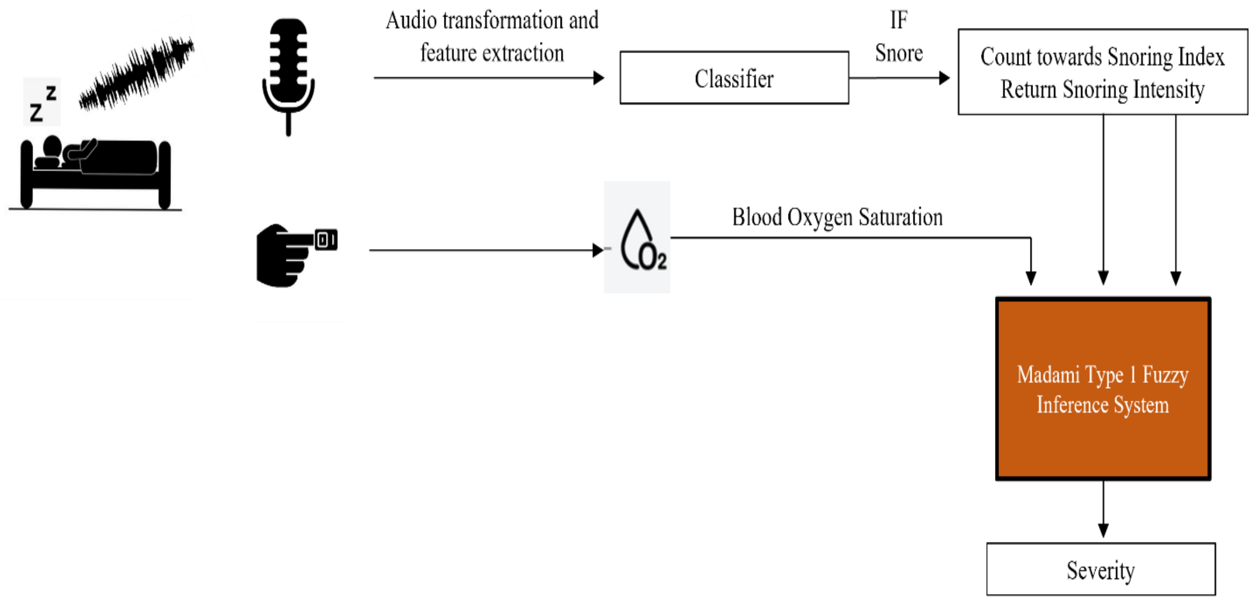

Figure 1Problem Blueprint

CHAPTER THREE: METHODOLOGY

Our research is divided into four tasks to form a model. The first task consists of the 1). snoring detection, 2). Spo2 readings 3). Fuzzy inference system, and 4). Hardware implementation. The following chapter will go into each of these sections in detail.

3.1 SNORING DETECTION

Audio signals are waveforms that measure the amplitude of a signal over time. However, it can be challenging for deep learning models to extract essential features due to their variation over time, making it difficult to find patterns in audio. To tackle this problem, the signal can be transformed from the time domain to the time-frequency domain by applying a Short-Time Fourier Transform (STFT). This formula allows us to better represent the frequency of a signal at each point in time. To go from the time domain to the time-frequency domain, we first need a Fast Fourier transform over several overlapping window segments of the signal to calculate the spectrum at each segment [23]. The result of this process leads to a spectrogram (Figure 2.) The time-frequency representation of a signal can be used as a 2D image and train a convolutional neural network to detect patterns and features related to snoring events.

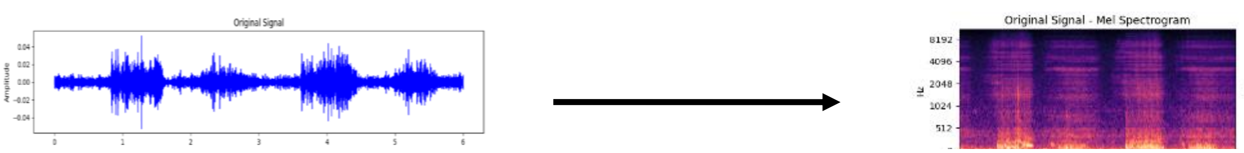

Figure 2 Representation of a signal in the time and time-frequency domain

The snoring detection methodology involves using spectrograms as input to a CNN. Spectrograms of shape (128, 151) are generated from audio files with a duration of 4 seconds and a sampling rate of 22.05kHz. The model was trained on an 80-20% split dataset consisting of 8632 labeled audios from the Urbansound8K dataset, which includes various urban sounds such as sirens, air conditioners, and children playing, among others [24], and 2500 wav files for non-snoring and snoring recordings provided by Milteneos [22] from his study in using deep neural networks to classify snoring and non-snoring episodes. To ensure proper balance in the classes, audio augmentation techniques were employed in the classes with fewer files. This included scaling the audio's pitch by four steps and reversing their polarity. This augmentation strategy helps create a more diverse and extensive dataset, leading to a better generalization [25].

The CNN architecture comprises four convolutional layers of 32, 64, 64, and 128 filters—three max-pooling layers of size 2x2 and a Rectified Linear Unit (Relu) activation function. The final convolutional layer is flattened and passed through two dense layers, followed by a dropout layer to counteract overfitting and an output layer with 12 classes and a soft-max activation function. The model is trained for 200 epochs with an initial rate of 0.001, an exponential decay rate of 0.96 staircasing over 100,000 steps, an Adam optimizer, and categorical cross entropy as the loss function. (Figure 2)

The objective of a snoring classifier is real-time inference to track the instances of snoring throughout the night. The snoring index, defined as three consecutive snoring episodes no more than 10 seconds apart, is calculated in real-time. Su Geun [17] established a correlation between the severity of AHI and the snoring index per hour. Average snoring indexes of 6.9 ± 5.9, 11.6 ± 7.5, 17.0 ± 8.9 and 31.5 ± 16.0 related to AHI < 5), mild (5 ≤ AHI < 15), moderate (15 ≤ AHI< 30) and severe (AHI≥ 30) OSA subgroups respectively. Calculating this index will be an essential aspect in classifying severity hourly. Another important feature extracted during audio detection is the average intensity of the windowed audio segment. This feature, representing the decibel level of snoring events, provides additional information for assessing sleep apnea severity as it too correlates with AHI indexes of normal, mild, moderate, and severe in 46.3 ± 3.6, 51.6 ± 4.8, 54.2 ± 5.2, and 60.5 ± 6.4 dB, respectively [19].

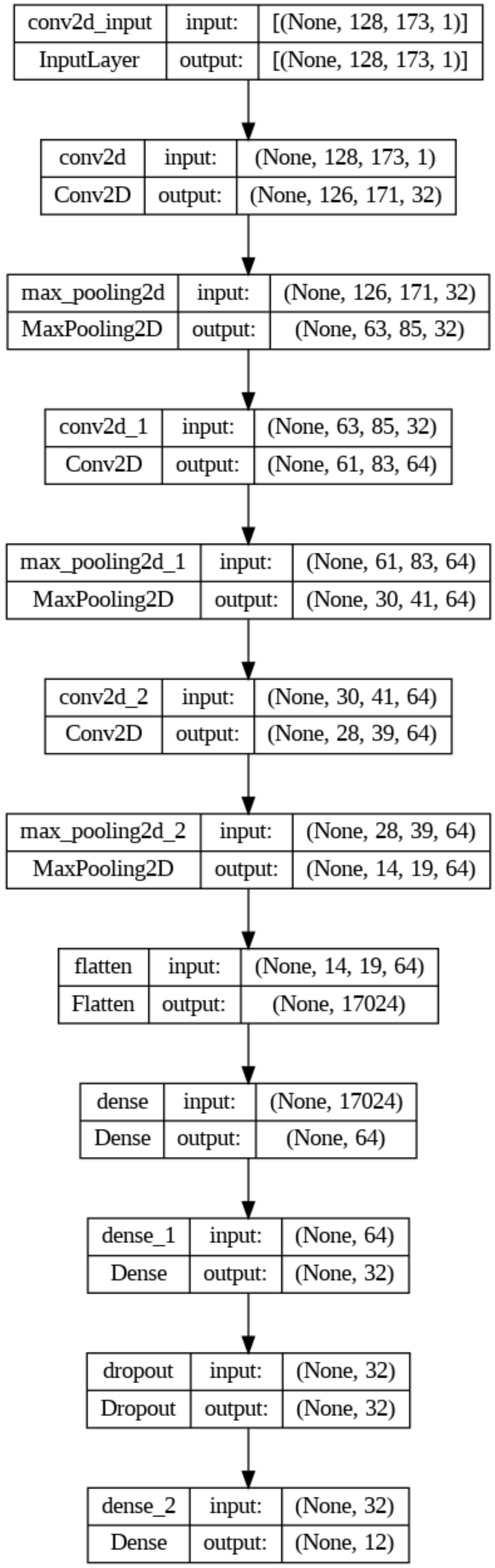

Figure 3 CNN Architecture

3.2 SPO2 READINGS

Pulse oximetry sensors are non-invasive methods for monitoring blood oxygen saturation levels. The sensor comprises an infrared (IR), a red LED, and a photodetector. The LEDs emit light through a user’s finger, penetrating red-colored tissue; the projection of light through the finger causes a reflection from the hemoglobin cells. (Fig 4) The photodetector measures the amount of light the blood reflects, and photodiodes convert the light signals into analog data. Analog data can be processed into blood oxygen percentage levels [25]. If the sensor is placed correctly, it will output constant and accurate readings. We can leverage this device to monitor Spo2 levels at night and extract the minimum readings every hour. Several Spo2 features directly correlate to AHI OSA severity. The desaturation index includes the number of oxygen desaturations per hour. Desaturation is defined as a decrease in 3% of the baseline levels, the minimum and average SpO2 values, and the percentage of desaturation below 90% during the whole sleep period [21]. Regarding our research, the chosen feature has been the minimum values of SpO2.

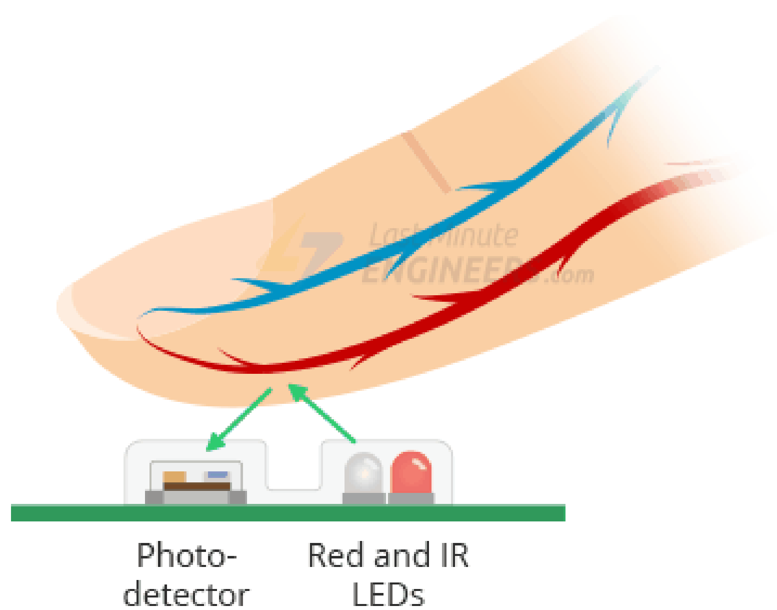

Figure 4 Oximetry Sensor [44]

3.3 Fuzzy Logic

Fuzzy logic aims to model human decision-making and reasoning where the truth of a statement is not reduced to binary values of truth or false. Fuzzy inference systems employ degrees of truth that range from zero to one. Zero is no correlation to the statement; one is a whole truth value. It lets us reduce uncertainty by fuzzifying inputs and using a human-designed set of rules, in most cases developed by an expert in the field [26]. It provides an excellent tool for any decision-making process, like determining the severity of the OSA when analyzing the selected snoring index, snoring intensity, and oxygen saturation features. These features have been shown to correlate to the different severities of AHI; however, there is no clear threshold to follow and give an accurate assessment. The means of each of the severity categories for each feature overlap with one another and complicate a decision process. If there were an agreed-upon definition of what levels of each feature, it would be simple to determine severity; however, the values overlap because they tend to vary from person to person. To mitigate this problem, we incorporate a fuzzy inference system that allows us to give degrees of truth to the inputs and establish membership functions within a universe discourse. We propose using fuzzy logic with the Snoring Index/hour, the average intensity of snoring, and the minimum SpO2 reading per hour to evaluate a patient's severity hourly in real-time. The fuzzy system comprises linguistic variables, membership functions, fuzzy rules, and a Mamdani inference engine. Mamdani was selected because it is well-suited when using human input and contains a more interpretable rule base.

The system consists of 3 inputs with triangular membership functions, each assigning degrees of truth to severity categories such as normal, mild, moderate, and severe, denoted in table 1. Membership functions describe the degree of membership of a value to the corresponding linguistic category. These membership functions are determined based on research findings determined by a range of average values observed in relation to patients diagnosed with different severities of OSA.

Table 1Input Membership Function

SpO2		Snoring Index		Snoring Intensity(dB)	
Normal	[94 95 101]	Normal	[-1 7 14]	Normal	[-1 46 51]
Reduced	[90 93 96]	Mild	[3 12 20]	Mild	[46 52 56]
Critical	[87 90 93]	Moderate	[6 17 28]	Moderate	[49 55 60]
Severe	[82 85 89]	Severe	[14 32 50]	Severe	[54 61 100]
Critical	[0 75 85]				

3.3.1 Snoring Index Membership Functions

The average frequency of snoring episodes a patient has throughout the night strongly positively correlates with the different classifications of AHI. Su Geun evaluated 5035 patients who visited a sleep clinic between March 2003 and December 2020 and observed that snoring frequency increased according to patients AHI severity diagnosis [17]. The mean snoring episode index was 6.9 ± 5.9 for primary snorers which had an AHI lower than 5. Based on this analysis a membership function that fell between this range was selected for “Normal” severity in Snoring index starting at-1 to give the value of 0 some degree of truth with normal OSA severity. Since the mean snoring index was set as 6.9, we selected the value of 7 as the peak for the “Normal” classification of severity. The higher range of primary snorer correlation falls at 12.8, similarly we selected a value of 14 as the higher range value with 0 degrees of truth to fully capture 13 as a number for the snoring index that still falls into some degree of truth inside the “Normal” category. Following this same reasoning, determined the rest of the degree of truth ranges for the triangular membership functions, setting the peak as the average found in Se-Geun's study and going one under and one over at the lower and higher values respectively to account the lower and higher ranges in the snoring index to be part of the assessment. The rest of the correlations were observed to be 11.6 ± 7.5 for patients with mild OSA AHI severity ranging from 5 ≤ AHI < 15, 17.0 ± 8.9 for moderate (15 ≤ AHI< 30) and 31.5 ± 16.0 for the severe (AHI≥ 30) OSA subgroup. The structure of the membership functions is depicted in figure 5.

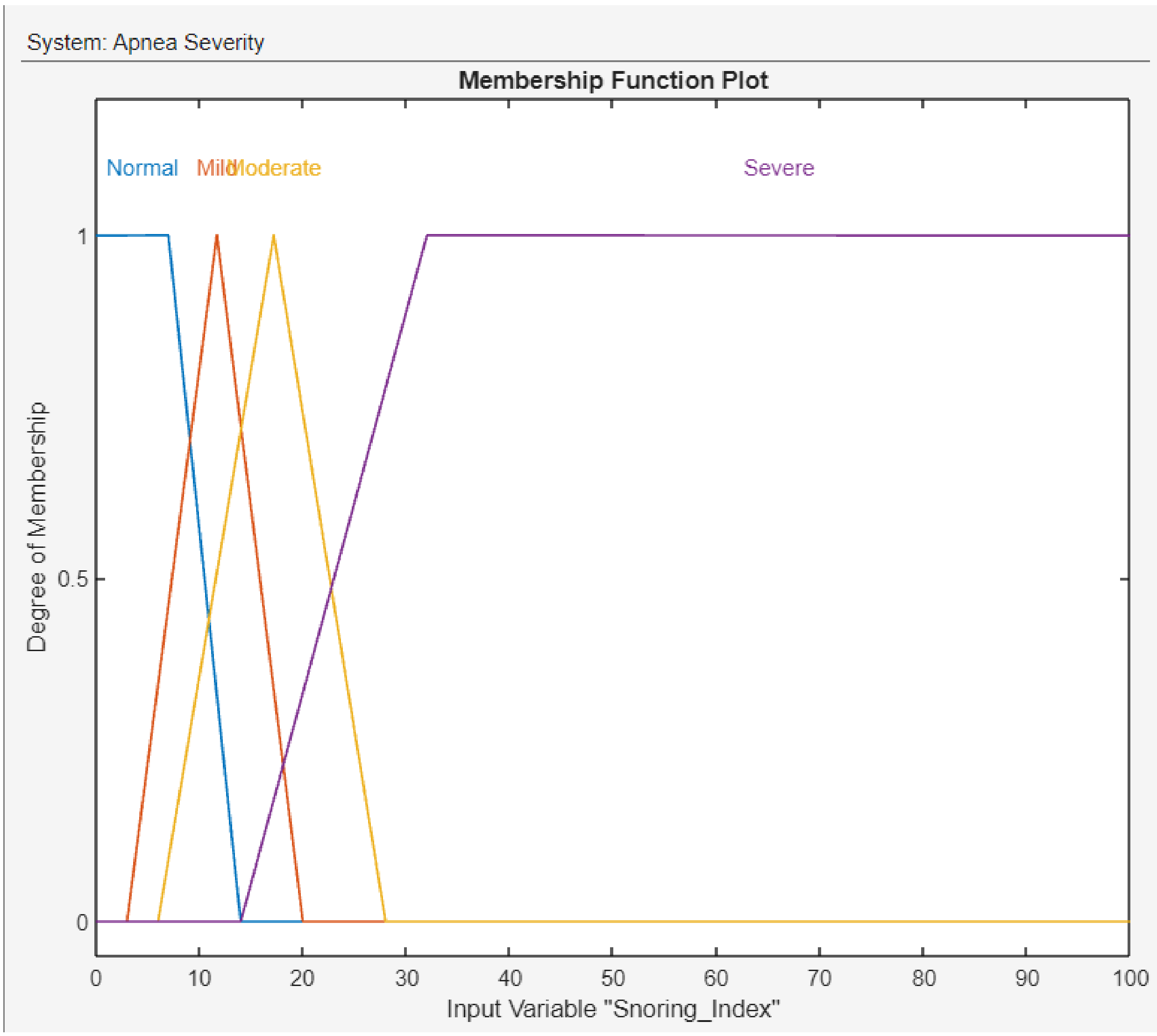

Figure 5 Snoring Index Membership Functions Plot

3.3.2 Snoring Intensity Membership Functions

Similarly, as with the snoring index, Maimon [19] studied 1643 habitual snorers and observed a high correlation between OSA AHI severity and snoring intensity ($r = 0.66$, $p < 0.01$). The mean apnea-hypopnea index increased across all categories of AHI and the intensity ranged between 46.3 ± 3.6 dB for patients with no OSA or lower than 5 AHI. The lower level of the membership function was selected to be -1 to have all intensities below the mean to enter inside the “Normal” category for our severity assessment. The peak was chosen as the rounded value of the mean, and the right most part of the triangular membership function was chosen as one unit more than the higher range from the mean associated in the study. This to make sure that the higher range value still lands within some degrees of truth inside the membership function. Continuing with this process, the study determines that the correlation continues with 51.6 ± 4.8 for mild OSA (AHI 5 to 15), 54.2 ± 5.2 for moderate OSA (AHI 15 to 30) and 60.5 ± 6.4 dB for severe OSA (AHI 30 to 50). Again, the peaks of the membership functions were selected as the mean of each range and the higher and lower ranges were crafted to ensure that the full ranges of the correlated values fall within the degrees of truth. For the severe classification the higher ranged value was selected as 100 to accommodate for any intensity that is louder than the ranges observed in the study to be included in the severe category. Figure 6 shows a visual representation of the membership functions for snoring intensity.

3.3.3 SpO2 Membership Functions

Finally, for oxygen saturation the observation between SpO2 indices and OSA severity was determined to correlate with several SpO2 parameters amongst 346 individuals that took polysomnography overnight [21]. Such parameters included the sum of all desaturations below 90%, the duration of respiratory events, the total indices of arousals and the minimum SpO2

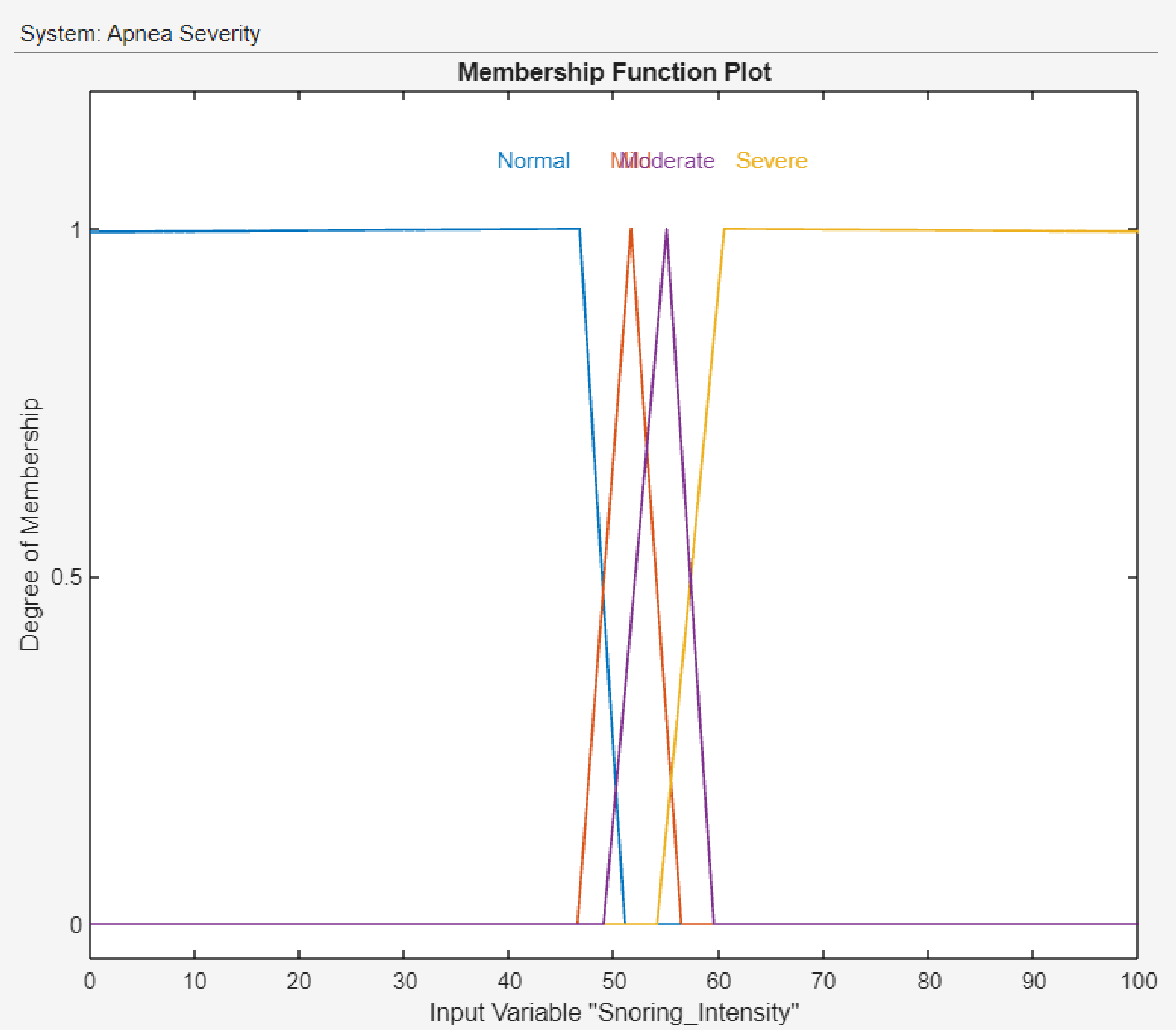

Figure 6 Snoring Intensity Membership Functions Plot

reading per hour. This last value was found to be inversely correlated with OSA severity at $P < 0.001$ indicating a high correlation. The study concluded the clinical reliability in using SpO2 readings to support OSA severity. Ranging from mild (AHI 5 – 15), moderate (AHI 15 – 30) and sever (AHI > 30) the minimum SpO2 values associated with the values were selected accordingly. In this scenario for a "normal" category since it was not indicated in the study, we selected an oxygenation rate that's considered to be healthy and with no desaturation that ranges between 96% and 100%. In addition, we have decided to include a critical category for oxygenation levels that fall under 75% because these demand immediate medical attention and they pose grave consequences. Depicted in figure 7 are the triangular membership functions plotted in space.

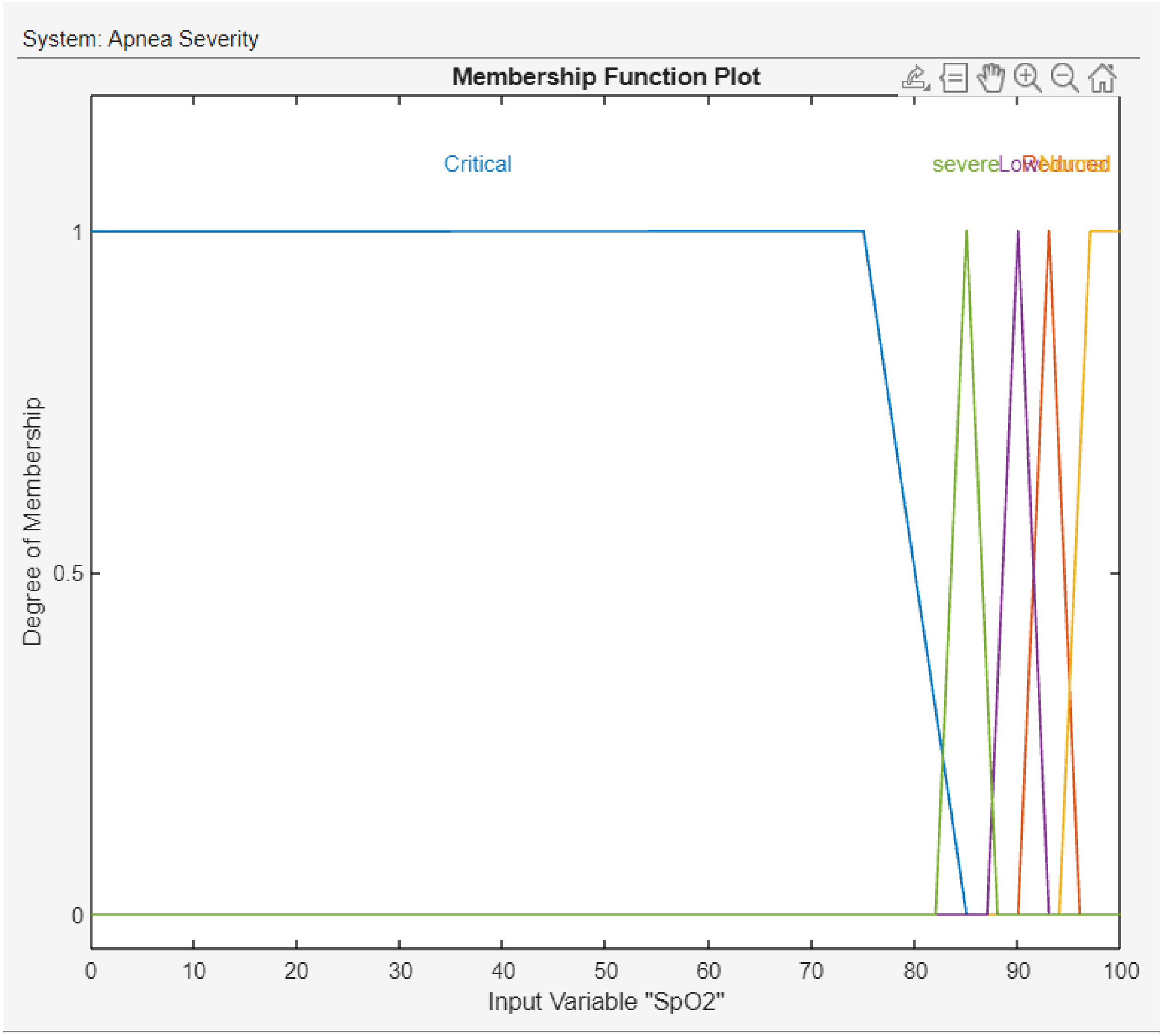

Figure 7 SpO2 Membership Functions Plot

3.3.4 Output Severity Membership Functions

Fuzzy rules are formulated to capture the relationship between inputs and the output, which represents the apnea severity. Rules play the role of combining degrees of truth to generate an overall assessment of severity. Mamdani engine processes the fuzzy rules and computes degree of membership for each category and develops a final crip output representing the hourly severity of sleep apnea symptoms (Figure 8). The membership functions for the output are represented in table 2 and the fuzzy rules can be found in the appendix. An integration with real time snoring detection that takes continuous audio signals allows for constant monitoring and hourly evaluations opening a path to enable timely intervention or adjustment to treatment strategies by working together with medical professionals. Following the three inputs into the Mamdani fuzzy inference they are deffuzyfied by a centroid method that returns a center of gravity of the fuzzy set to find the perfect balance. The output was selected to be evenly distributed amongst five categories (Normal, Mild, Moderate, Severe and Critical) (Figure 9) with the Critical category as the selection when the fuzzy inference system outputs a value greater than 0.96. Critical values only are selected when the value for minimum blood oxygen levels fall below 75% in the hopes of giving the user's a suggestion of seeking immediate medical attention.

Table 2 Output Membership Functions

Severity Category	Membership Functions
Normal	[0 0 0.2]
Mild	[0 0.2 0.4]
Moderate	[0.35 0.5 0.7]
Severe	[0.65 0.8 0.96]
Critical	[0.95 1 1]

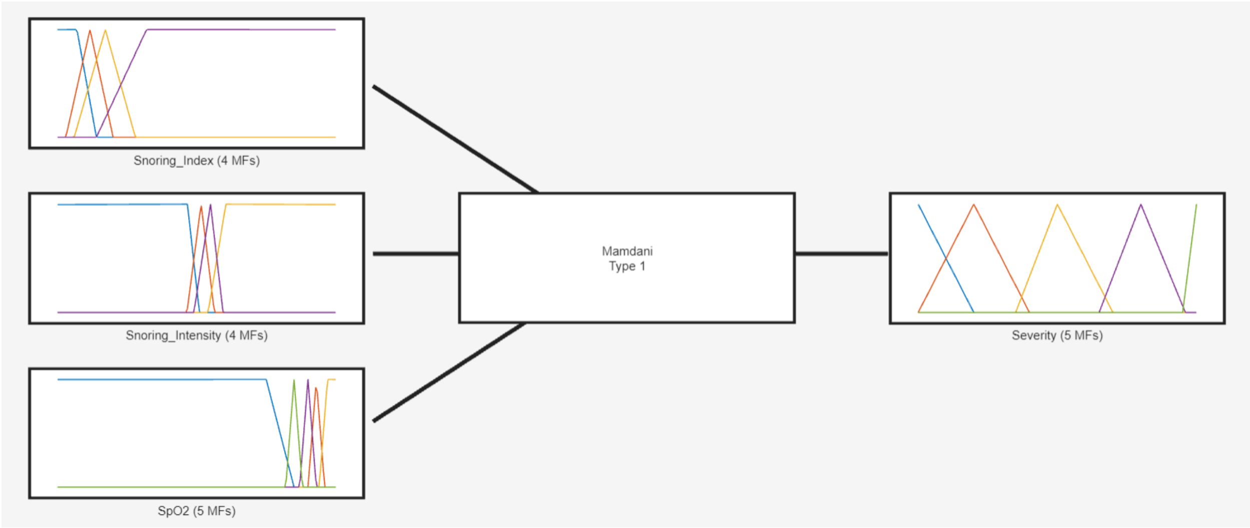

Figure 8 Fuzzy Logic Inference System

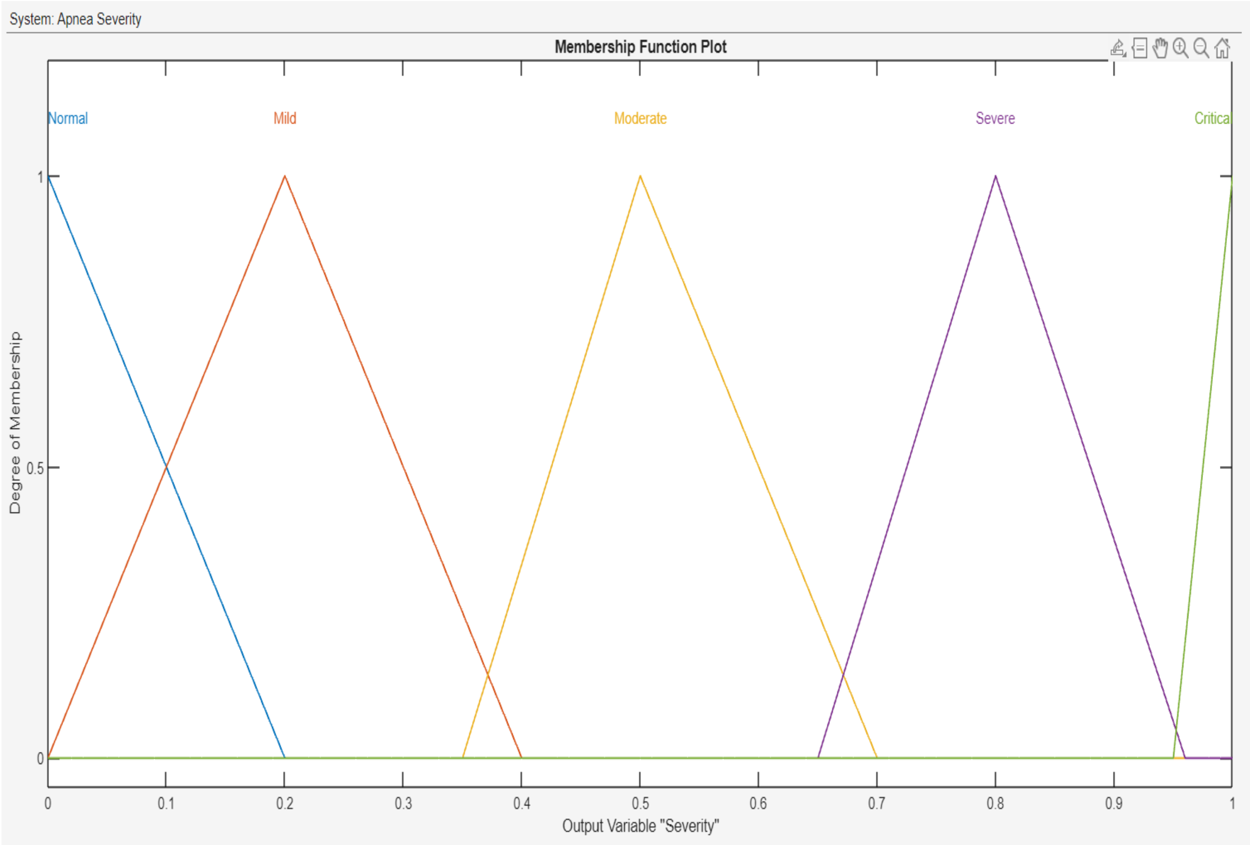

Figure 9 Severity Output Membership Function

The outputs of the membership functions are determined by an inference made on a set of rules developed in an if then format to mimic human decision making. The development of these rules was given certain inputs higher impact when rules encountered difference in categories. Such rules gave higher priority to blood oxygen levels as oxygen desaturation is a common symptom often looked at in polysomnography tests. The second highest priority was given to snoring index because even though high frequency in snoring correlates with OSA, we know that not all snoring is determined to be OSA and due to the configuration of our design there is room for misclassification of snoring. Finally, the category with the least priority was given to snoring intensity as the values between the categories are the ones that overlap the most making intensity the most uncertain. The set of rules used for the decision-making process are concentrated in table 3.

Table 3 Fuzzy Rules

Fuzzy Rules Sleep Apnea Severity
1. If (Snoring_Index is Mild) and (Snoring_Intensity is Normal) and (SpO2 is Reduced) then (Severity is Mild)
2. If (Snoring_Index is Moderate) and (Snoring_Intensity is Normal) and (SpO2 is Reduced) then (Severity is Mild)
3. If (Snoring_Index is Severe) and (Snoring_Intensity is Normal) and (SpO2 is Reduced) then (Severity is Moderate)
4. If (Snoring_Index is Normal) and (Snoring_Intensity is Mild) and (SpO2 is Reduced) then (Severity is Normal)
5. If (Snoring_Index is Mild) and (Snoring_Intensity is Mild) and (SpO2 is Reduced) then (Severity is Mild)
6. If (Snoring_Index is Moderate) and (Snoring_Intensity is Mild) and (SpO2 is Reduced) then (Severity is Moderate)
7. If (Snoring_Index is Severe) and (Snoring_Intensity is Mild) and (SpO2 is Reduced) then (Severity is Moderate)
8. If (Snoring_Index is Normal) and (Snoring_Intensity is Severe) and (SpO2 is Reduced) then (Severity is Mild)
9. If (Snoring_Index is Mild) and (Snoring_Intensity is Severe) and (SpO2 is Reduced) then (Severity is Mild)
10. If (Snoring_Index is Moderate) and (Snoring_Intensity is Severe) and (SpO2 is Reduced) then (Severity is Moderate)
11. If (Snoring_Index is Severe) and (Snoring_Intensity is Severe) and (SpO2 is Reduced) then (Severity is Severe)
12. If (Snoring_Index is Normal) and (Snoring_Intensity is Moderate) and (SpO2 is Reduced) then (Severity is Mild)
13. If (Snoring_Index is Mild) and (Snoring_Intensity is Moderate) and (SpO2 is Reduced) then (Severity is Mild)

Table 3 Continued

14. If (Snoring_Index is Moderate) and (Snoring_Intensity is Moderate) and (SpO2 is Reduced) then (Severity is Moderate)
15. If (Snoring_Index is Severe) and (Snoring_Intensity is Moderate) and (SpO2 is Reduced) then (Severity is Severe)
16. If (Snoring_Index is Normal) and (Snoring_Intensity is Normal) and (SpO2 is Normal) then (Severity is Normal)
17. If (Snoring_Index is Mild) and (Snoring_Intensity is Normal) and (SpO2 is Normal) then (Severity is Normal)
18. If (Snoring_Index is Moderate) and (Snoring_Intensity is Normal) and (SpO2 is Normal) then (Severity is Mild)
19. If (Snoring_Index is Severe) and (Snoring_Intensity is Normal) and (SpO2 is Normal) then (Severity is Moderate)
20. If (Snoring_Index is Normal) and (Snoring_Intensity is Mild) and (SpO2 is Normal) then (Severity is Normal)
21. If (Snoring_Index is Mild) and (Snoring_Intensity is Mild) and (SpO2 is Normal) then (Severity is Normal)
22. If (Snoring_Index is Moderate) and (Snoring_Intensity is Mild) and (SpO2 is Normal) then (Severity is Moderate)
23. If (Snoring_Index is Severe) and (Snoring_Intensity is Mild) and (SpO2 is Normal) then (Severity is Moderate)
24. If (Snoring_Index is Normal) and (Snoring_Intensity is Severe) and (SpO2 is Normal) then (Severity is Mild)
25. If (Snoring_Index is Mild) and (Snoring_Intensity is Severe) and (SpO2 is Normal) then (Severity is Mild)
26. If (Snoring_Index is Moderate) and (Snoring_Intensity is Severe) and (SpO2 is Normal) then (Severity is Moderate)
27. If (Snoring_Index is Severe) and (Snoring_Intensity is Severe) and (SpO2 is Normal) then (Severity is Moderate)
28. If (Snoring_Index is Normal) and (Snoring_Intensity is Moderate) and (SpO2 is Normal) then (Severity is Normal)
29. If (Snoring_Index is Mild) and (Snoring_Intensity is Moderate) and (SpO2 is Normal) then (Severity is Mild)
30. If (Snoring_Index is Moderate) and (Snoring_Intensity is Moderate) and (SpO2 is Normal) then (Severity is Moderate)
31. If (Snoring_Index is Severe) and (Snoring_Intensity is Moderate) and (SpO2 is Normal) then (Severity is Moderate)
32. If (Snoring_Index is Normal) and (Snoring_Intensity is Normal) and (SpO2 is Low) then (Severity is Mild)
33. If (Snoring_Index is Mild) and (Snoring_Intensity is Normal) and (SpO2 is Low) then (Severity is Mild)
34. If (Snoring_Index is Moderate) and (Snoring_Intensity is Normal) and (SpO2 is Low) then (Severity is Moderate)
35. If (Snoring_Index is Severe) and (Snoring_Intensity is Normal) and (SpO2 is Low) then (Severity is Severe)
36. If (Snoring_Index is Normal) and (Snoring_Intensity is Mild) and (SpO2 is Low) then (Severity is Mild)
37. If (Snoring_Index is Mild) and (Snoring_Intensity is Mild) and (SpO2 is Low) then (Severity is Mild)

Table 3 Continued

38. If (Snoring_Index is Moderate) and (Snoring_Intensity is Mild) and (SpO2 is Low) then (Severity is Moderate)
39. If (Snoring_Index is Severe) and (Snoring_Intensity is Mild) and (SpO2 is Low) then (Severity is Severe)
40. If (Snoring_Index is Normal) and (Snoring_Intensity is Severe) and (SpO2 is Low) then (Severity is Moderate)
41. If (Snoring_Index is Mild) and (Snoring_Intensity is Severe) and (SpO2 is Low) then (Severity is Moderate)
42. If (Snoring_Index is Moderate) and (Snoring_Intensity is Severe) and (SpO2 is Low) then (Severity is Severe)
43. If (Snoring_Index is Severe) and (Snoring_Intensity is Severe) and (SpO2 is Low) then (Severity is Severe)
44. If (Snoring_Index is Normal) and (Snoring_Intensity is Moderate) and (SpO2 is Low) then (Severity is Mild)
45. If (Snoring_Index is Mild) and (Snoring_Intensity is Moderate) and (SpO2 is Low) then (Severity is Moderate)
46. If (Snoring_Index is Moderate) and (Snoring_Intensity is Moderate) and (SpO2 is Low) then (Severity is Moderate)
47. If (Snoring_Index is Severe) and (Snoring_Intensity is Moderate) and (SpO2 is Low) then (Severity is Severe)
48. If (Snoring_Index is Normal) and (Snoring_Intensity is Normal) and (SpO2 is severe) then (Severity is Moderate)
49. If (Snoring_Index is Mild) and (Snoring_Intensity is Normal) and (SpO2 is severe) then (Severity is Moderate)
50. If (Snoring_Index is Moderate) and (Snoring_Intensity is Normal) and (SpO2 is severe) then (Severity is Moderate)
51. If (Snoring_Index is Severe) and (Snoring_Intensity is Normal) and (SpO2 is severe) then (Severity is Severe)
52. If (Snoring_Index is Normal) and (Snoring_Intensity is Mild) and (SpO2 is severe) then (Severity is Moderate)
53. If (Snoring_Index is Mild) and (Snoring_Intensity is Mild) and (SpO2 is severe) then (Severity is Moderate)
54. If (Snoring_Index is Moderate) and (Snoring_Intensity is Mild) and (SpO2 is severe) then (Severity is Severe)
55. If (Snoring_Index is Severe) and (Snoring_Intensity is Mild) and (SpO2 is severe) then (Severity is Severe)
56. If (Snoring_Index is Normal) and (Snoring_Intensity is Severe) and (SpO2 is severe) then (Severity is Severe)
57. If (Snoring_Index is Mild) and (Snoring_Intensity is Severe) and (SpO2 is severe) then (Severity is Severe)
58. If (Snoring_Index is Moderate) and (Snoring_Intensity is Severe) and (SpO2 is severe) then (Severity is Severe)
59. If (Snoring_Index is Severe) and (Snoring_Intensity is Severe) and (SpO2 is severe) then (Severity is Severe)
60. If (Snoring_Index is Normal) and (Snoring_Intensity is Moderate) and (SpO2 is severe) then (Severity is Moderate)
61. If (Snoring_Index is Mild) and (Snoring_Intensity is Moderate) and (SpO2 is severe) then (Severity is Moderate)

Table 3 Continued

62. If (Snoring_Index is Moderate) and (Snoring_Intensity is Moderate) and (SpO2 is severe) then (Severity is Severe)
63. If (Snoring_Index is Severe) and (Snoring_Intensity is Moderate) and (SpO2 is severe) then (Severity is Severe)
64. If (Snoring_Index is Normal) and (Snoring_Intensity is Normal) and (SpO2 is Reduced) then (Severity is Normal)
65. If (SpO2 is Critical) then (Severity is Severe)

3.4 Hardware Implementation

The proposed model involves the integration of a MAX30102 (Figure 10) to a raspberry pi with a microphone connection to facilitate real-time assessments. The MAX30102 sensor is coupled with a breadboard connected to a Raspberry Pi 4B using jumper wires. The connection diagram is shown in (Figure 11).

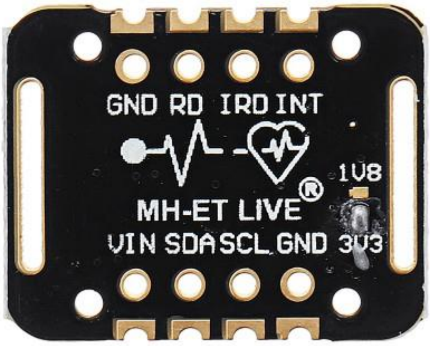

Figure 10 MAX30102[44]

To establish a proper connection, the following connections are made.

- Vin (MAX30102) to Pin 1(3.3V): to provide power to the sensor.
- SDA(MAX30102) to Pin 3(SDA): this connections is used for bidirectional transfer of data between devices.
- SCL(MAX30102) to Pin 5(SCL): SCL is a serial clock line responsible for synchronizing data between devices.
- INT(MAX30102) to Pin7(GPIO): The interrupt is used to signal when new data is ready to be read by the raspberry pi, it is also used to activate interrupts for events as well as put the device in sleep mode if no readings are being made.
- GND to Pin9(GND): Ground pin.

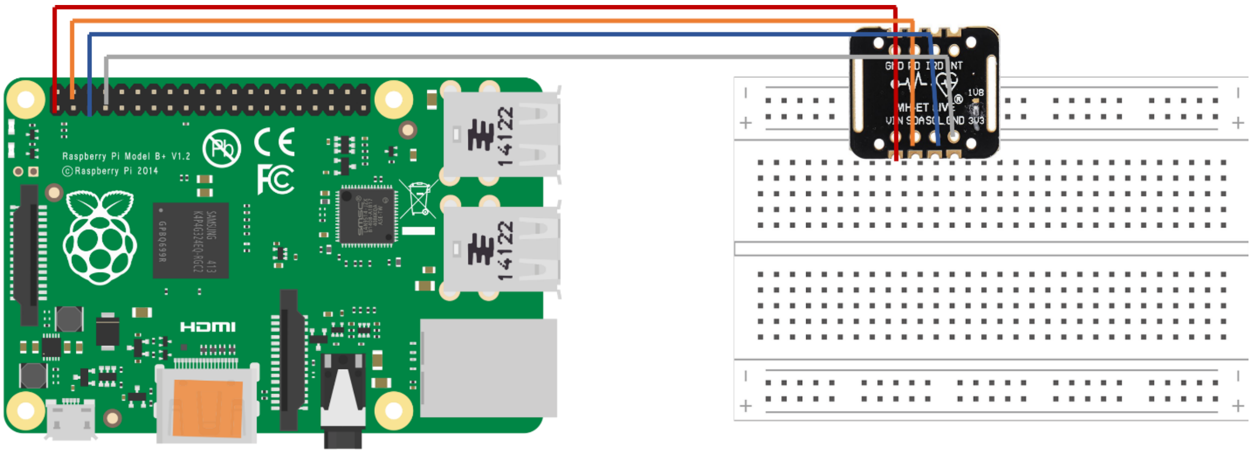

Figure 11 Sensor Board Connection

A regular USB microphone is connected to the Raspberry Pi's USB port to capture live audio data. Live audio input and continuous sensor reading are implemented simultaneously by threading the programs together, allowing parallel deployments. From the microphone, we run the snoring detection algorithm to keep count of the snoring index by setting a timestamp for every snoring event encountered by the classifier. Suppose the difference between subsequent timestamps for the next snoring detection episode is less than 10 seconds. The snoring event is counted as a consecutive snoring episode. If three consecutive snoring episodes are achieved, the consecutive snoring episodes contribute to one score to the snoring index. The average intensity of the snoring episodes detected is also stored for further analysis in the fuzzy inference system; the complete structure of the application is depicted in (Fig 12). Improvements to this work should include a BLE sensor to enable communication between the sensor and CPU without physical connections.

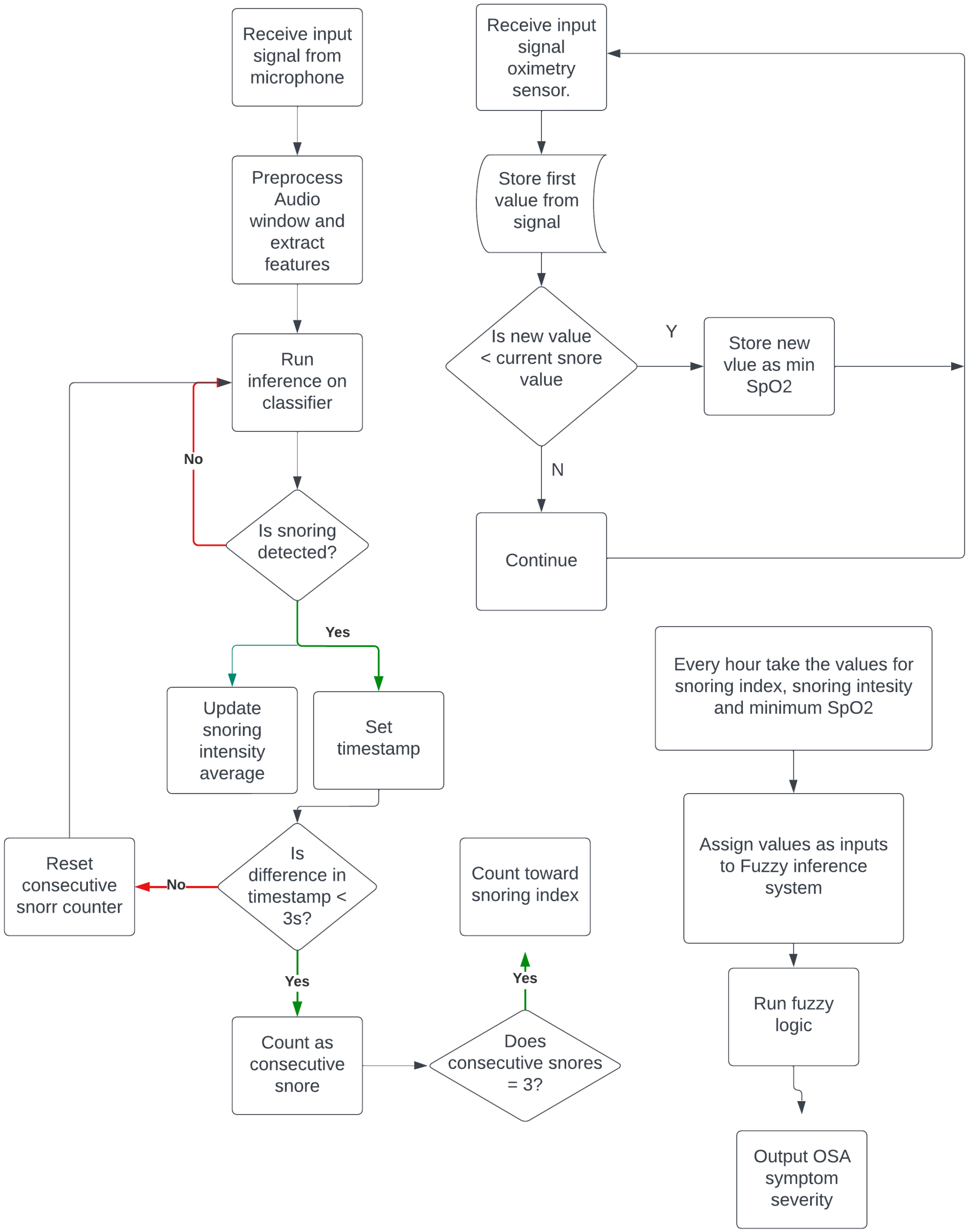

Figure 12 System Flowchart

CHAPTER FOUR: RESULTS

This chapter presents the study's outcomes, centering on real-time assessment of sleep apnea severity through the integration of convolutional neural networks for snoring detection and a fuzzy logic system for severity classification.

4.1 Convolutional Neural Network Performance

= The CNN demonstrated exemplary performance in discriminating between snoring and familiar urban sounds, reaching a testing accuracy of 86.7%. The model exhibits consistent convergence over time, as illustrated in (Fig 13a, 13b) depicting accuracy and loss metrics across epochs. The convergence shows no indications of overfitting. From this analysis we can determine that convolutional neural networks effectively find the important features of sound and accurately classify events. The ability to classify snoring events lays a foundational role in the proposed approach.

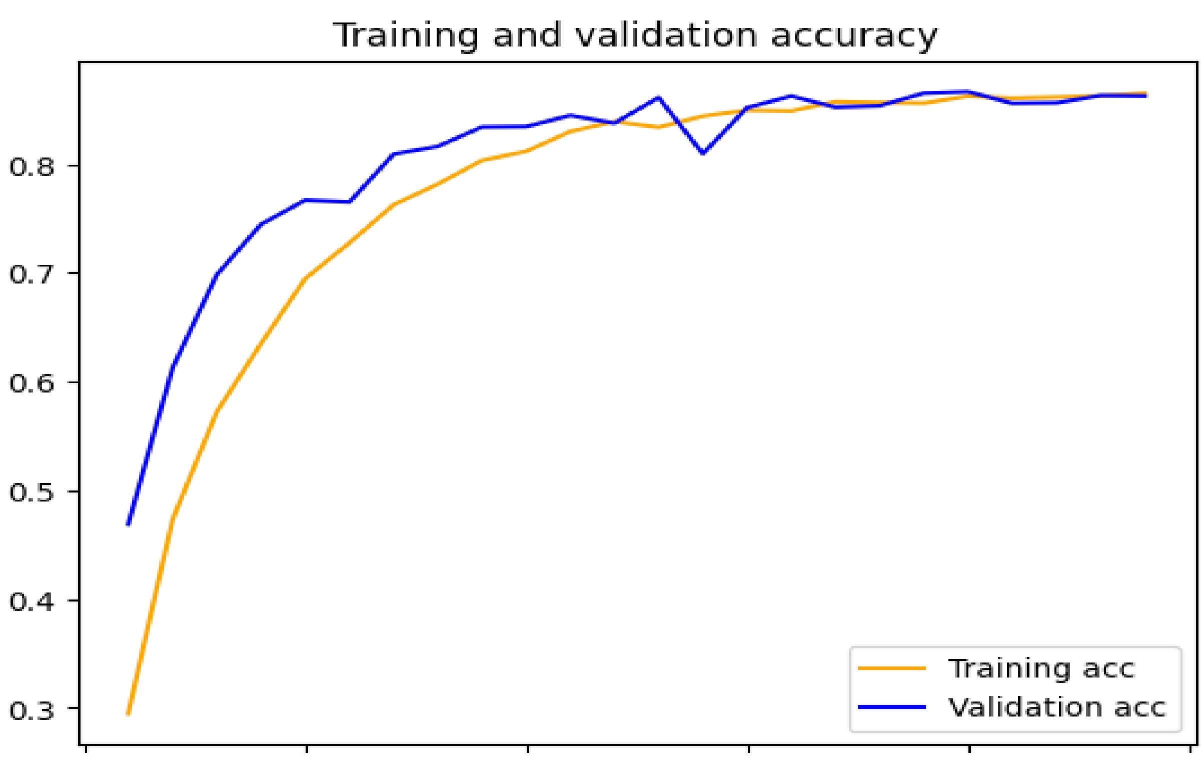

Figure 13a CNN Training and Testing Accuracy Metrics

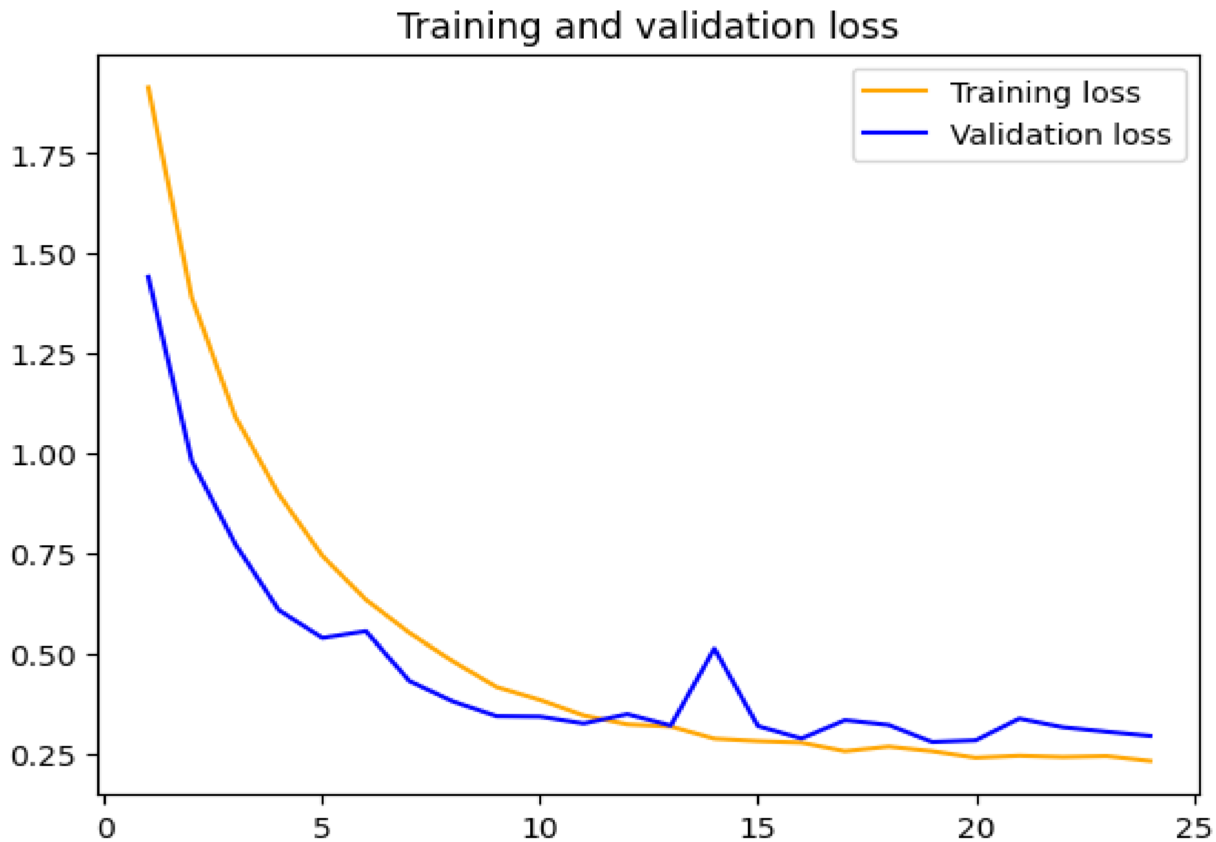

Figure 13b Training and Testing Loss Metrics

4.2 Fuzzy Logic System for Severity Classification

The Fuzzy Logic System demonstrated efficacy in processing the linguistic variables from inputs. Simulated data was generated randomly from the three inputs to test different scenarios. The random values were chosen from a range of estimated values found in each input category. For the snoring index values between 0 and 60 were randomly assigned and coupled with random values between 30 and 75 that are the average intensity values found in snoring and all fall between the ranges selected for the membership functions and blood oxygenation levels were selected from ranges covering from 70 and 100.

The Mamdani engine efficiently translates the fuzzy inputs into crisp values of severity assessment, providing a flexible and interpretable approach to classifying sleep apnea (Table 4).

Integrating the CNN for snoring detection and the fuzzy logic system for severity classification forms a comprehensive approach to real-time sleep apnea severity assessment. Leveraging the strengths of both models aims to provide accurate and timely evaluations, enhancing the potential for early intervention and risk mitigation. Further evaluation needs to be conducted with real annotated data from medical professionals to determine the model's performance and adjust accordingly.

Table 4 Fuzzy Logic Results

Snoring Index	Avg_Snoring_Intensity	Min_Oxygen	Severity	Severity Category
31	51.87139091	99.53708144	0.2	Normal
45	32.39065263	90.19212464	0.65	Moderate
24	37.28527989	84.84124694	0.6725017	Moderate
44	49.38770627	86.93072865	0.8	Severe
19	74.97698141	95.27013792	0.315140514	Mild
1	31.34118645	83.35207696	0.277064885	Mild
4	33.81655558	99.67638026	0.063335142	Normal
58	45.94367001	80.51280245	0.962812536	Critical
53	72.20916141	99.37437981	0.2	Normal
9	74.17963901	76.17846877	0.969274399	Critical
13	30.70315867	76.19335884	0.96926011	Critical
38	32.32429132	86.8810701	0.8	Severe
30	67.07507813	76.16018761	0.969291922	Critical
34	49.78492563	94.82852906	0.35	Mild
5	53.3353768	85.69035955	0.354647458	Mild
10	42.86100383	78.14890785	0.966923119	Critical
41	56.17121017	95.66911284	0.2	Normal
48	56.26366561	75.72972921	0.969596614	Critical
52	69.33120592	81.41190612	0.961001604	Critical

CHAPTER FIVE: DISSCUSSION

This study aimed to develop a real time sleep apnea severity classification of its common symptoms such as frequency of snoring, snoring intensity, and oxygen saturation metrics. Our results indicate that developing a neuro-fuzzy model is a practical approach to estimating severity of symptoms. The CNN model achieved consistent convergence and accuracy of 86.7%, proving that CNNs are a valuable tool in sound event classification. However, extracting features such as Mel Spectrograms is a resource-extensive procedure leading to latency and increased risk of data leakage. The CNN model performs well on sounds that pertain to the training data given, but it is necessary to continue evaluating into how well it will perform in generalizing to unseen sounds and how well it can perform on noisy data. It is essential to further the research into different models that permit sound classification through raw data to minimize the model's inference time and latency to results. An exciting approach in improving the model's generalization is using self-attention provided by transformers that enable the model to learn the positional information of the analyzed audio. Approaches in using respiratory data to classify snoring events is also promising and will deal with misclassifications due to background noises or unideal microphone placements.

The fuzzy logic outputs correlate reasonably with the cases presented and integrate effectively when deployed into an edge device. It is worth noting that the evaluation of the fuzzy system was done on purely simulated data and the rules have been determined based on research conducted, leaving room for improvement. Working alongside medical professionals to help determine a more efficient set of rules would improve the models' inference immensely. After the recollection of data, the fuzzy logic system can be adapted from a Mamdani engine to a Sugeno engine to enable an Adaptive Neuro Fuzzy inference system that takes input data and uses neural networks to determine the best degrees of truth for the membership functions as well as improvements to the correlations of rules. A current hourly assessment is beneficial for continuously monitoring the severity of symptoms, however further research should focus on determining the minimal optimal timeframe window to give an accurate assessment and perform actions more frequently.

The edge device is a powerful tool that enables data from sensors to perform real time evaluations, they are compact and with BLE Sensors can be incorporated into comfortable casings for everyday use.

CONCLUSION

Sleep apnea obstruction syndrome (OSA) is a pressing health concern that needs to gain awareness as its diagnosis remains under 20%. It is a common contributing factor to deaths due to heart disease and, proper assessment should be attainable to anyone. While polysomnography tests are effective, they require extensive time and economic resources. Our proposed approach aims to bring the user closer to a severity assessment by classifying frequent symptoms according to AHI guidelines. The model shows good performance with simulated data.

In conclusion, our study marks a step forward in developing tools for severity awareness with a CNN and a fuzzy logic system. Our findings offer practical implications for the healthcare industry, emphasizing the potential for early detection and personalized management.

Future work should include research on more manageable solutions for snoring detection in the form of Transformers with self-attention to reduce inference speeds or training deep learning models on respiratory signals to avoid misclassification.

The fuzzy logic system should be sought to improve decision-making rules by working alongside medical professionals who help determine the best course of action. Accurate data should be gathered, and the model should be reevaluated to test performance. The symptoms of sleep apnea vary depending on severity but can also vary from person to person depending on age, gender, BMI, and neck circumference. Upcoming work should focus on taking these metrics into account to make more personalized assessments. Finally, the models should be deployed with BLE sensors for comfortable and efficient user interaction.

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