Flinders University

College of Science and Engineering

A SMART SUPINE AVOIDANCE ALARM DEVICE FOR THE TREATMENT OF SUPINE PREDOMINANT OBSTRUCTIVE SLEEP APNOEA

Thesis submitted to the College of Science and Engineering in partial fulfilment of the requirements for the degree of Master of Engineering (Biomedical) at Flinders University, Adelaide, Australia

Submitted by

Anand Subramaniam – subr0065

Student ID: 2218527

Supervisor: Prof. Peter Catcheside

Supervisor: Dr. Sherry Randhawa

Date of Submission: 2nd November 2020

Declaration

I hereby certify that the work on 'A Smart Supine Avoidance Alarm Device for the Treatment of Supine Predominant Obstructive Sleep Apnoea' does not incorporate without acknowledgment, any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge it does not contain any material previously published or written by another person except where due reference is made in the text.

Anand Subramaniam

8th November 2020

Acknowledgement

I would like to express my humble gratitude towards my Supervisors, Prof. Peter Catcheside and Dr. Sherry Randhawa for all the support and guidance provided for successfully completing this project. I would also like to express my special thanks to Mr. Matthew Rahimi from Adelaide Institute of Sleep Health for all the help and insights provided for this project without which the research would not be complete. I sincerely thank Dr. Stuart Wildly, the topic coordinator and his team for organizing this topic and for all the support provided over this year. Finally, I am very thankful to Flinders University and the Adelaide Institute of Sleep Health for providing me with such an opportunity and for all the facilities provided for the successful completion of this project.

Executive Summary

The objective of this project is to develop a smart supine avoidance positional therapy device for treating Obstructive sleep apnoea Research conducted on this topic identified the potential of positional therapy in treating Obstructive Sleep apnoea (temporary cessations in breathing during asleep) and the current flaws in the process. The major flaw associated with this technique is the variable efficacy and lack of sleep parameter monitoring for measuring the success of the therapy. These shortcomings are believed to keep positional therapy inferior to the first line therapy called continuous positive airway pressure (CPAP) that delivers high pressure to act as a pneumatic splint to prevent airway collapse, although CPAP is intrusive in nature and expensive and have a poor patient adherence for long term therapy.

The project deliverables are created to improve the current position therapy technique by integrating sleep parameter monitoring functions. Snoring was identified as the primary parameter for monitoring as it closely correlates to OSA. The aim of the project is to design a smart alarm based PT device that detects supine posture and user snoring to send vibro-tactile feedback to avoid chances of OSA by changing the sleep posture. In addition, a sound data logger attached to the device stores the snoring frequencies that can be plotted externally to derive snoring and apnoeic events.

The design was tested to measure the output success. The test results helped identify system errors and optimal parameters for different detection algorithms that were improved over time. The final test result showed considerable project success by producing expected results with an snoring detection accuracy of 0.84, specificity and sensitivity of 0.74 and 0.94 respectively. The limitations of the project were identified in the process to improve device over further works. The future directions of this project were stated to design a sleep monitoring and treatment system that can be an equivalent to CPAP for treating OSA.

TABLE OF CONTENTS

List of Figures

List of Tables

List of Abbreviations:

AHI	Apnoea-Hypopnoea Index
AISH	Adelaide Institute for Sleep Health
ANN	Artificial Neural Networks
BMI	Body Mass Index
CPAP	Continuous Positive Airway Pressure
ESS	Epworth Sleepiness Scale
FOSQ	Functional Outcomes of Sleep Questionnaire
MPP	Mattress and Pillow for Prone positioning
OSA	Obstructive Sleep Apnoea
POSA	Positional Obstructive Sleep Apnoea
PSG	Polysomnography
PT	Positional Therapy
RDI	Respiratory Disturbance Index
SBE	Snore/Breathing Episodes
TBT	Tennis-Ball Technique

Chapter 1: Introduction

Obstructive sleep apnoea (OSA) is increasingly common and chronic sleep related disorder characterized by the obstruction in breathing by the periodic narrowing of the pharyngeal airway in sleep (Peppaerd et al. 2013). The World Health Organisation in 2007 estimated more than 100 million people were affected by OSA globally (World Health Organization 2007). Over ten years, Resmed showed that the scale almost increased by ten folds predicting a total of 963 million people affected by OSA in 2018 (Marin-Oto et al. 2019). In 2010, the Sleep Health Foundation estimated 775,000 people in Australia (4.7% of population) suffered from OSA, that was more than half of the total sleep disorders estimation in the country and the annual cost of treating OSA was estimated to be $21.2 billion (Sleep Health Foundation 2011). A seminal study (Simpson et al. 2013) pointed out that one in every ten Australians are subjected to undiagnosed OSA; out of which population of males affected are more than females, about 49% males aged 40-69 years and in males aged over 70 years it can be as high as 62%.

Almost 60% of clinically significant OSAs are undiagnosed (Benjafield et al., 2018). Untreated OSA can lead to many long-term health consequences like metabolic disorders, cardiovascular diseases and depression; they are also a leading cause of motor vehicle accidents that may lead to fatality and productivity loss (Howard et al. 2004). The first line therapy for OSA is CPAP (Continuous Positive Airway Pressure) which is an effective treatment that uses air pressure delivered via a nasal cannula to create a pneumatic stent that prevents airway collapse, but the patient adherence to this method is unacceptably low because of its intrusive nature (Olsen et al. 2008). Although non-CPAP therapies like oral appliances, airway surgery and weight loss are beneficial in selected cases, they still have variable efficacy. Positional therapy (PT) involves supine avoidance during sleep to treat position predominant OSA and have been a successful technique for treating OSA as more than 50% of clinically significant OSA is positional and occur only in the supine posture (Obomomi & Quan 2018, pp. 297). A recent study by Obomomi, Olabimpe and Quan (2017) proved that PT is an effective long term treatment for OSA but also pointed out that PT remains inferior to CPAP only because of its inability to continuously monitor sleep parameters relating to respiratory events.

The risks associated with undiagnosed and untreated OSA and the net cost of treatment can be reduced by treating it early. Positional therapy is regarded as an effective and cheaper solution for treating mild to severe OSA (Mok et al. 2019). Oksenberg et al. (2014) proved that for a long term treatment, PT devices have better patient adherence than CPAP.

This project aims to overcome the shortcoming of PT by developing a smart supine avoidance device that supports the recording of an additional snoring parameter that can be used for the continuous monitoring of sleep health and frequency of OSA events. The snoring detection can also be used for a smart alarm device that can alert the user when snoring, that could reduce user snoring frequency and avoid the development of OSA. Such a device can prove to be equivalent to CPAP and be a first line therapy for positional OSA that can be comfortable for the user as it is non-intrusive. Such a system is expected to reduce the net cost of treating OSA compared to CPAP while improving the patient adherence to treatment.

Chapter 2: Literature Review

2.1. Obstructive Sleep Apnoea

Obstructive sleep apnoea (OSA) is the most common clinical problem of breathing in sleep characterised by frequent episodes of partial or complete upper airway obstruction during sleep (Lowe et al. 1996). OSA is strongly associated with sleep fragmentation, oxygen desaturation, hypercapnia and markedly increased breathing efforts and frequent surges in sympathetic nervous system activity that may place individuals at greater hypertension, heart attack and stroke risks (Sleep Health Foundation 2011, p. 08). OSA is often defined on the basis of the presence of five or more obstructive episodes per hour of sleep (Robert Basner 2007, p.1751). OSA is caused by the periodic narrowing of pharyngeal airway in sleep that obstructs airflow, most commonly in nasopharynx as shown in Figure 2.1 (Motamedi et al. 2009; Osman et al. 2018). Other features of OSA include snoring, interrupted respiratory patterns in sleep, fatigue and loss of concentration resulting from irregular sleep (Motamedi et al.2009). Kato et al. (2009, p.1363) estimated that more than 85% of clinically significant OSA patients have never been diagnosed. Untreated OSA is also associated with long term health consequences including cognitive impairment, metabolic disorders and cardiovascular disorders (Kato et al. 2009).

The pathogenesis of OSA is multifactorial and include both, anatomical and non-anatomical neuromuscular, arousal and respiratory factors (Eckert et al. 2018; Carberry et al. 2017), although anatomical factors are thought to play the major role (Victor 1999). Obesity, facial malformations, thickening of pharyngeal walls, macroglossia, nasal congestion and tonsillar hypertrophy are amongst the main physical attributes that can contribute to OSA (Victor 1999, Basner 2007). Nasopharygeal muscles acutely relax when OSA patients fall asleep which can result in the surrounding tissues to collapse compromising the airway (Motamedi et al. 2009) as shown in Figure 2.1. Reduced ventilation leads to carbon dioxide accumulation and oxygen desaturation in the blood and chemoreflex stimulation of breathing effort that contribute to frequent arousals (Kato et al. 2009; Victor 1999). Whilst arousals promote a burst of nasopharyngeal muscle activity helping to open the airway (Kato et al. 2009), this response is only transient and hyperventilation associated with arousal and airway re-opening may promote low breathing and upper airway muscle activity promoting the next cycle of obstruction and arousal. OSA is typically worse while patient sleep in the supine position due to gravitational effects on the airway (Lowe et al. 1996).

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Figure 2.1: Normal vs obstructed airway
Normal airway (left) with normal uvula and soft palate. Obstructed airway in sleep (right) with enlarged and elongated palate obstructing the posterior airway and an enlarged tongue pushed by a retruded jaw to obstruct hypopharyngeal space (Victor 1999)

Non-anatomical contributors to OSA include a low respiratory arousal threshold (patients are easily awoken when the airway narrows), high loop gain resulting from unstable ventilatory control and ineffective pharyngeal dilator activity in sleep (Carberry, Amatoury & Eckert 2018, p. 744).

2.1.1. **Diagnosis and Treatment**

The standard sleep disorder diagnosis is based on in-laboratory polysomnography (PSG) from which the primary outcome is the apnoea-hypopnoea index (AHI) used to define OSA and severity. AHI represent the average number of breathing cessations (apnoeas) or significant airflow reduction (hypopnoea) lasting ten seconds or more leading to >3% O_2 desaturation or arousal (Osman et al. 2018). Based on the AHI, sleep apnoea can be classified into mild (5 - 15 AHI), moderate (15 - 30 AHI) and severe (> 30 AHI) (Osman et al. 2018, p. 22).

OSA treatments include CPAP, positional therapy, oral appliances, weight loss and airway surgery. CPAP is the first line therapy for OSA, and uses pressure delivered through a nasal or oronasal mask to increase pharyngeal cross-sectional area by acting as a pneumatic splint to prevent collapse (McEvoy et al. 2016). CPAP may also help to improve airway function by increasing expiratory lung volume, increasing axial tension on the airway through anatomical tethering effects, and through reduced loop gain through increased gas stores in the lung (Squier et al. 2010). Oral appliances can be a useful first- or second- line therapy for OSA in some patients, although treatment success is more variable compared to CPAP. Oral appliances generally work by moving the retruded tongue and palate forward to help increase retro-palatal space and stiffen the pharyngeal tissue to avoid airway collapse (Ng et al. 2003). Weight loss can also successfully treat OSA in many patients where obesity plays an important causal role in OSA. For example, Young et al. (2005) estimated that excess body weight was responsible for 41% of mild OSA and 58% of moderate to severe OSA in US adults. The two main forms of weight loss for OSA involve medical weight loss and surgical weight loss (Sutherland et al. 2011). Medical weight loss uses a factor or a combination of factors that include low-calorie diet, pharmacological agents and changes in lifestyle. Surgical weight loss can be performed through bariatric surgery and is generally reserved for patients failing nonsurgical weight loss options and also for patients with BMI above 35 kg/m^2 (Carberry, Amatoury & Eckert 2018). Airway surgery is sometimes performed to treat OSA, generally following failure of other treatments as a salvage therapy (Mackay and Chan 2016). Nasal surgery can also help to improve the efficacy of other treatments, by reducing nasal resistance to improve the tolerance and effectiveness of CPAP (Camacho et al. 2015). However, all of the currently available main treatments for OSA are associated with significant problems that limit their use and effectiveness. A summary of key limitations of OSA treatments by Carberry et al (2018) is presented in Table 2.1, which in the main include problems of tolerance and acceptance (e.g. CPAP), and variable efficacy likely reflective of different causal mechanisms in individual patients and smaller treatment effect-sizes compared to CPAP.

A recent study (Osman et al. 2018, p21) highlights the main problems of poor adherence of OSA patients to first-line CPAP therapy and also the unpredictable efficacy of non-CPAP therapies, highlighting the need for new and improved approaches for OSA treatment.

Table 2.1: Different procedures for OSA treatment and limitations associated with them (Carberry, Amatoury & Eckert 2018)

PROCEDURE	LIMITATIONS
CPAP	It is intrusive in nature and uncomfortable leading to low tolerance and compliance.
Oral Appliances	Demands frequent visits to dentists and is expensive proving to have variable efficacy. Low patient adherence due to unwanted dental changes and mandibular pain.
Weight Loss	It works for a minority of cases with mild OSA. Achieving substantial weight loss is hard and can be even harder to maintain.
Airway Surgery	Costly and present unpredictable efficacy Subject to risks like anaesthesia complications and infection. Can also be painful

2.2. Positional therapy

Positional obstructive sleep apnoea (POSA), where OSA is only a clinically significant problem when patients sleep on their back, is prevalent and affects around 50% of OSA patients (Cartwright et al. 1991). POSA is typically defined on the basis of clinically significant OSA (AHI greater than 5), where the supine AHI is at least twice that of non-supine AHI (Cartwright et al. 1991; van Maanen & de Vries 2014). Another, potentially more clinically useful definition, also requires a non-supine AHI below the cut-off used to define OSA, such that these patients would not be classified as OSA patients if they could successfully avoid supine sleep.

Positional therapy (PT) refers to OSA treatments that aim to prevent sleep apnoea by avoiding the supine position during sleep. Although this approach can be effective, several diagnostic factors and short-comings of PT for treating POSA have been identified in previously reported literature. A summary of key relevant studies and their main findings are presented in Table 2.2 and outlined below.

Dandan et al. (2018), using a cross sectional regression analysis of PSG data from 243 patients over 18 years old found a significantly reduced probability of identifying OSA in patients with lower supine sleep time during PSG compared to patients with higher supine sleep, irrespective of BMI, age or cardiac condition. Thus, sleep position during a diagnostic PSG, which may or may not be reflective of how patients usually sleep at home, importantly influences diagnostic decisions and has the potential to contribute to false positive and negative diagnoses.

Benoist et al. (2016) studied the effects of PT for residual POSA management post upper airway surgery in 33 post-operative patients using a PT device that detects supine posture and uses vibratory feedback to the user to discourage supine sleep. 12 patients (37.5%) were classified as responders and when treated for 3 months showed an overall reduction in both epworth sleepiness scale (ESS) score and AHI determined via repeat PSG. Patients also showed improved minimum oxygen saturation from reduced supine sleep. From the 37.5% responders 31.3% were recorded with treatment success. Furthermore, device measured compliance with PT was high, with 89% of patients using the device for > 4 hours a night for 5 or more days in a week. The study indicated that the addition of PT to patients with post-operative residual POSA can improve the therapeutic effectiveness.

A seminal study by Bidarian-Moniri et al. (2015) examined OSA treatment using prone positioning by performing two-night separate PSG night studies on 32 patients using a mattress and pillow to encourage prone positioning (MPP). The first night involved normal sleep positioning on normal beds and the second night using the mattress and pillow for prone positioning (MPP). 27 patients completed the study and it was observed that the median AHI and ODI decreased from 23 to 7 and from 21 to 6 respectively. From the 27 patients 17 (63%) patients were considered responding to prone positions, 12 of 15 with POSA (80%) and 5 of 12 as non-POSA (42%).

Bignold et al. (2009) investigated patient self-reported long-term acceptance and adherence to traditional tennis-ball treatment (TBT) for discouraging supine sleep using a pouch and tennis ball strapped to the back in patients previously provided with TBT over a 4 year period at the

Adelaide Institute for Sleep Health (AISH). Out of 108 patients identified to have received TBT, 67 patients completed a follow-up questionnaire regarding their treatment experiences. Only 6% (4 patients) reported continued use of TBT. A further 13.4% (9 patients) reported not using TBT because they felt they had learned to avoid supine sleep without continued treatment. The remaining 80.6% (54 patients) reported abandoning the use of TBT, principally because the technique was too uncomfortable for most patients.

Bignold et al. (2011) performed another study using a PT device that performs both position monitoring and supine-avoidance via vibration alarm feedback to the wearer (BuzzPOD, Gorman Promed, Australia). This light weight device is strapped to the chest and produces a strong vibration alarm to discourage the supine position, and also logs and stores posture changes and alarms over night for subsequent download via USB communication. 15 patients completed a one-night in-laboratory sleep study using an infrared camera to confirm accurate body position of the device. In a small group of patients who used the device for several weeks at home, the device was used all night on most nights available for use and the alarm was highly effective in reducing supine time in most patients.

In a study by DeVries et al. (2015), follow-up polygrams where conducted on 40 patients treated with PT using TBT for 12 weeks. 27 patients showed significant reductions in AHI and improvement in oxygen saturation supporting treatment utility. Despite treatment success for reducing AHI, treatment compliance was poor and diminished over time with 26 of the 40 patients abandoning therapy after only a few months of treatment.

Van Maanen et al. (2014) performed a similar but larger study using a vibrational PT device (Somnibel sleep position trainer by Sibelmed) that monitors and stores position data and uses a vibration alarm on the forehead when the device detects the supine position. From 145 POSA patients recruited into the study, 106 completed the study which showed significantly reduced supine sleep at 6 months. 64.4% of patients showed device usage for more than 4 hours per night, although this reduced to 46.9% of patients when patient drop outs (patients who abandoned treatment) were taken into account. Functional Outcomes of Sleep Questionnaire (FOSQ) and ESS questionnaires at the start of the study and at one, three and six months into the study showed improved sleep related quality of life in this patient group, supporting treatment benefits with this form of therapy.

The same device was used in a more recent study by Armas et al. (2019) of twelve OSA patients from OSI Araba University Hospital, who underwant baseline and followup PSG studies over a four week treatment period. The median AHI was reduced with the use of the PT device and there was some evidence to support that device usage helped to condition patients to avoid the supine posture prior to device vibration.

The efficacy of a neck worn vibratory PT device (Night Shift, Advanced Brain monitoring Inc) that discourages the supine posture was assessed by Levendowski et al. (2014) in 30 OSA patients. This device is strapped to the back of the neck and detects sleep position and sends vibro-tactile feedback using two haptic motors from the main unit. The device also stores snoring signals using an inbuilt microphone. Baseline PSG findings were compared with follow up PSG after at least 4 weeks of use, and showed noticeable improvement in sleep continuity, reduced AHI (Table 2.1) and improved self-report sleep and depression scores following treatment.

The same group performed another study (Levendowski et al. 2018) using the same device to measure patient compliance and behavioural adaptation to supine-avoidance over time via a retrospective analysis of behavioural adaptation to vibrotactile PT in 135 patients over a period of 15 – 52 weeks. Overall, 71% of patients using the device showed average device usage of more than 4 hours a night. However, long term user compliance was relatively poor given the total number of users reported at the final week was only 35 of 135 and almost 92% of non-compliant patients remained so after the initial 12 weeks. In addition, use of device largely failed to improve snoring with only 5 patients showing decreased snoring frequency, 5 showing increased snoring frequency and the remainder (91 %) showing no change in snoring frequency. This study shows that for a particular population, the device did not affect snoring.

In a retrospective study Jackson et al. (2015) randomized 86 patients into two groups; a control group who received sleep hygiene advice alone and an active treatment group who received a TBT device along with sleep hygiene advice. Sleep hygiene included information regarding lateral sleep positioning, weight loss and exercise and a follow up PSG was conducted after 4 weeks in both groups. Repeat PSG studies showed a significant reduction in AHI and supine sleep in the active compared to the control group, but with no significant reduction in daytime sleepiness or improved quality of life.

Heinzer et al. (2012) performed PSGs on 16 POSA patients treated with a novel form of TBT that included an embedded actigraphic motion monitoring device for objective assessment of device usage over 3 months. Comparisons of baseline and end-of-study PSGs demonstrated a significant reduction in supine sleep time, oxygen desaturation and AHI. Furthermore, 73.3% of patients used the device for 8 ± 2 hours per night based on actigraphic monitoring, supporting relatively high treatment acceptance and usage.

Table 2.2: Summary of all studies and evidence of prevalence of PT

Study	**Year**	**PT Device/ Therapy**	**Supine Sleep time**	**Supine sleep time with PT**	**Baseline AHI**	**AHI with PT**	**Sleep Efficiency (%)**	**Sleep efficiency with PT (%)**
Bignold et al.	2009	TBT	42.5 % ± 26.8 %	7.9 ± 13.9	22.1 ± 14.9	7.3 ± 5.5	n/a	n/a
Bignold et al.	2011	Buzzpod	36.6 % ± 5.7%	19.3 % ± 4.3 %	25	13.7	n/a	n/a
Heinzer et al.	2012	TBT	42.8 ± 26.2	5.8 ± 7.2	26.7 ± 17.5	6 ± 3.4	n/a	n/a
Levendowski et al.	2014	Night Shift	46.4 % ± 12.7 %	2.2 % ± 6.1 %	24.7 ± 14.7	7.5 ± 7.7	80.9 ± 11.9	85.1 ± 7.6
Van Maanen et al.	2014	Somnibel	49.9 %	3 %	16.4	5.2	n/a	n/a
Bidarian et al.	2015	MPP	142 Min	< 1[a] min	23	7	n/a	n/a
De Vries et al.	2015	TBT	155.3 min	33.5 min	14.5	5.9	n/a	n/a
Jackson et al .	2015	TBT	130.9 min	28.4 min	20.1	10.8	76.3	75.5
Benoist et al.	2016	Somnibel - Sleep position trainer	40.1 %	7.4 %	18.3	12.5	90.8	89.5
Levendowski et al.	2018	Night Shift	58.6%	6.8%	n/a	n/a	80	83.4
Armas et al.	2019	Somnibel	51.5 % ± 14.8 %	25.2 % ± 21 %	30.7	21.5	84.3	87.3

In short, PT devices have been shown to effectively reduce supine sleep and AHI in POSA patients. Several different approaches, using different PT devices to discourage supine sleep, support that non-discomfort vibrational feedback for supine avoidance is preferable to non-vibratory supine discomfort or position-restrictive devices like TBT and MPP that physically limits patient movement in sleep. These non-vibratory devices appear to exhibit varying levels of comfort, acceptance and tolerability that effects the efficacy and/or compliance and thus the long-term acceptability and effectiveness of PT therapy. Substantial variability and limited improvements in daytime sleepiness and quality of life may also limit the utility of PT for long-term management of POSA. A further and largely unexplored drawback of PT may be limited effectiveness in reducing snoring given that most PT devices do not evaluate snoring, and minimal changes in snoring in those PT devices that do log snoring.

On the other hand, a retrospective analysis by Ramos et al. (2015) supports that PT can be effective and cost-saving compared to CPAP, which has excellent efficacy but poor patient acceptance and compliance that limits long-term tolerance and effectiveness. This analysis of patient treatment preferences showed that of 42 patients, 6 chose weight management, 1 an oral appliance and in the remaining 35 patients, 12 patients underwent PT for POSA and the remaining 23 patients were treated using CPAP. The average cost of treatment was estimated to be $289.95 per patient for PT compared to $962.49 for CPAP, more than 3 times the average cost for PT.

2.3. Snoring and OSA

Snoring is one of the earliest, most common and problematic features of OSA for patients and their bed-partners, and is a very common problem for many individuals without clinically relevant OSA (Jin et al. 2015). Snoring is one of the primary reasons for patients to seek clinical sleep assessment and treatment and one of the more easily accessible signals compared to other physiological signals for screening OSA (Marin 2012), although standardised methods for defining and measuring snoring remain lacking. Nevertheless, problem snoring is reported in up to 94% of OSA patients (Young et al. 1993). “Snoring is the warning bell of partial or impending airway collapse, whereas OSA occurs with a complete airway obstruction lasting longer than 10 seconds” (Prinsell 2012, p.1048), although this statement is not strictly correct since OSA is defined on the basis of both partial and complete airway obstruction events where hypopnoeas (i.e. partial obstruction events likely to be associated with transient snoring and noisy gasping following arousal) are usually much more common than complete apnoea events. However, snoring and OSA are highly correlated. For example, Rodrigues et al. (2010) compared a Stanford classification of snoring versus AHI in 168 patients diagnosed with OSA and found a strong positive correlation between snoring intensity and OSA severity, where loud and intense snorers were more likely to be diagnosed with moderate to severe OSA.

Another cross-sectional study (Ferini-Stambini et al. 1999) investigating the relationship between snoring and sleep apnoea in a cohort of 365 middle-aged females among whom 19.7% were reported to be every night snorers, 7.1% snored more than 50% of nights and 54.2% for more than 10% of nights. A significant correlation between the percentage of nights with snoring and AHI was identified, although 50% of study participants who snored more than half of the sleep period showed no evidence of clinically significant sleep apnoea. This study concluded that a high percentage of snoring is not necessarily associated with occurrence of sleep apnoea in middle aged women, although snoring and sleep apnoea are very common.

In another population study, Bearpark et al. (1995) measured snoring and apnoea in 294 Australian men between 40 and 65 years using a MESAM IV home sleep monitoring system. These authors found a relatively low correlation between snoring time and AHI, but that both snoring and sleep apnoea are extremely common in middle aged Australian men. Nevertheless, similar to Ferini-Stambini et al. (1999) this study also found that snoring does not necessarily indicate the presence of apnoea but that the intensity of snoring can be suggestive of apnoeic events.

A more recent study (Alshaer et al. 2019) used advanced signal processing and machine learning algorithms to more objectively quantify relationships between sleep apnoea and snoring. This study, conducted in 235 patients with mean±SD snoring index (SI) of 320.2 ± 266.7 snores/h and AHI was 20.2 ± 18.8 /hr found that snoring could be accurately quantified with acoustic analysis of breath sounds. The investigation indicated that the overall correlation between AHI and SI was weak but significant. Furthermore, increasing OSA severity was associated with a stepwise increase in SI such that SI could potentially help to inform regarding both positive and negative diagnosis of OSA.

Thus, snoring has been identified as an important feature of OSA, although snoring detection alone is not sufficient for a conclusive diagnosis of OSA which requires other parameters from PSG. The project reported in this thesis drew inspiration from established limitations of current positional therapy treatments, where alarms simply respond to supine positioning, without the use of other signals to more specifically alarm to problematic breathing or snoring in supine sleep. Consequently, the aim was to produce an improved PT device that is smarter compared to existing models and is able to log both position and snoring and to more specifically alarm to supine positioning with fewer nuisance alarms during wake or unnecessary alarms during supine sleep in the absence of snoring unlike the other devices like Buzzpod and Night Shift that sends vibratory feedbacks purely based on supine detection.

2.4. Neural network based approach for snore detection:

Artificial neural networks (ANN) have been extensively employed to perform snore detection and apnoea monitoring over the years. Studies employing neural network based snore detection or apnoea detection or both are detailed below to outline how previous studies have used ANN for sleep parameter detection relevant to this project.

Emoto et al. (2012) proposed an ANN based approach for the automated identification of snore/breathing episodes (SBEs). The proposed model involved real time acquisition of sound data from the sleep environment and a snore classification based on ANN. The proposed model was validated clinically. From the clinical data, it was concluded that the model can detect SBE with a sensitivity of 0.892 and specificity of 0.874 even at times when the snoring signal was suppressed by background noise.

A study (Dafna et al. 2013) involved PSG sessions on 25 subjects using a directional condenser microphone at a distance of one meter from the subjects. The sessions produced more than 76,600 acoustic episodes that were grouped into snoring and non-snoring episodes by three scorers. The predictions were performed using AdaBoost classifier trained and validated against labelled acoustic episodes. The average rate of detection calculated using a ten-fold cross validation method was 98.4%. On testing the predictor model over the test group, the accuracy was measured to be 98.2% with a specificity of 98.3% and sensitivity of 98%. This analysis method allowed snore sound detections over a full night to provide quantified snore measures for patient follow-ups.

Nakano et al. (2014) developed a smartphone-based prototype for snore signal monitoring and to quantify OSA severity and snoring. This method used a smart phone attached to the chest over the sternum to monitor ambient sound using the built-in microphone along with FFT in real time for analysis. The PSG data of 50 subjects were collected, out of which data from 10 patients was used for creating the program and the rest were used for the validation process. The test results showed high correlation between the snoring time measure by the smart phone and the PSG. The respiratory disturbance index from the smartphone also correlated with AHI from the PSG and showed a sensitivity for OSA diagnosis of 0.70 and specificity of 0.94. However, the trials conducted for this study was based on a controlled environment and the use of such a prototype in a noisy home environment is unproven.

Shin & Cho (2014) used an in-built recording system of a smartphone to perform snoring detection in sleep through a custom smartphone application. Sound recordings were conducted in 10 individuals during sleep and the experiment also included a variety of other noises including talking, running a fan, coughing and music to simulate a realistic real-world sleep environment. A total of 44 snoring and 75 noise datasets were tested. Sound features where examined using a format analysis based on frequency and magnitude followed by a quadratic classifier to differentiate snoring and non-snoring events. Tests using a ten-fold cross validation algorithm showed 95.1% accuracy with sensitivity and specificity of 98.6% and 94.6% respectively.

A study by Nguyen & Won (2015) proposed a correlational filter multilayer perceptron network (f-MLP) with the first layer of the network operating in the frequency domain. The proposed network included an additional back propagation method in training compared to the ordinary-MLP (o-MLP). The use of back propagation allowed the network to self-adapt to produce output with more discrimination power for higher layer classifications. On applying the new network with backpropogation to snoring detection, the accuracy of detection increased to 96% from 82%.

Study by Khan (2019) aimed to develop and test a wearable snore detection and avoidance device, with positional snoring and avoidance the main device use scenario. A deep learning model was developed for snore detection that was transferred a listener module embedded system. This was used to develop a wearable gadget to detect snoring and send vibrational feedback to the upper arm of the user until the shift in sleep position from supine to the sides. A smart phone application was also designed to store snoring data for clinical analysis. The test results for the device showed 96% accuracy for the snoring detection model.

Table 2.3: Prevalence of Neural network based snoring detection

Study	Year	Accuracy (%)	Sensitivity	Specificity
Emoto et al.	2011	n/a	0.892	0.872
Dafna et al.	2013	98.2	98.3%	98%
Nakano et al.	2014	n/a	0.70	0.94
Shin & Cho	2014	95.07	98.58%	94.62%
Nguyen & Won.	2015	96	n/a	n/a
Khan	2019	96	n/a	n/a

The Table 2.3 summarises the studies conducted to identify the ANN based approach to snore detection. It is evident from the table that neural network algorithms for snoring detection have considerable accuracy and almost 0all tests showed good sensitivity and specificity. The prevalence of neural network in previous models of snoring detection is the motivation for the use of ANN based detection approach followed in this thesis. The thesis also consider the important parameters of ANN like inclusion of backpropagation correlating to improvement of the detection and the testing scenarios of aforementioned studies to be used for implementing and testing the snore detection algorithm.

Summary:

Obstructive sleep apnoea is closely related to high health risks like diabetes, heart diseases and loss of concentration leading to accidents, all these factors are indirectly linked to increasing mortality (Benjafield et al. 2018). Although the first line therapy, CPAP and other substitute techniques are successful in treating OSA, they have a low patient adherence and efficacy stating the need of a different technique for treatment. Since a majority of OSA is positional, PT therapies are an efficient replacement for treating OSA, by avoiding supine sleep positions while asleep preventing OSA. PT techniques and devices have improved over the years and have proved to successfully reduce patient AHI for treating OSA (shown in Figure 2.2). However, the current supine-avoidance devices designed to prevent supine position irrespective of apnoea episodes, lack alarm-specificity and are observed to cause nuisance alarms (alarms when the patients are having a healthy sleep on their back or while the patient is awake) leading to low patient acceptance and adherence. A smarter alarm-specific PT device is likely to improve this shortcoming. Although a range of previous studies have attempted to perform snoring detections (discussed in Section 2.4) this has not yet used to improve PT devices. Thus, the purpose of the work presented in this thesis was to prototype a next-generation smart PT device to combine position monitoring and recording with more clinically useful and specific alarm behaviour designed to only alarm when specifically indicated by snoring (which is also caused by an airway obstruction and is the primary sleep parameter for monitoring OSA), to help better monitor supine snoring and OSA avoidance efficacy to reduce nuisance alarms unlike previous models that purely depend on sleep positions for feedbacks and only concentrate on storing snoring sounds like the Night Shift.

Chapter 3: Methodology

The method of development was grouped into three main algorithms: Position monitoring, Snoring detection and Data logging, all together presented the final prototype. The position monitoring algorithm performs the sleep position detection similar to previous models using a gyroscope output. The snoring detection algorithm integrated to the model is perhaps the most important aspect of the project and is based on artificial neural networks that monitor sleep sounds and classifies snoring from the data for user alarm feedback. The data logging algorithm store the sound signals for diagnosis and clinical studies after use making sleep studies more convenient than before. This chapter discuss in detail the approach on developing the three major algorithms and integrating them for the final prototype.

3.1. Position Monitoring

Monitoring sleep position to avoid supine sleep is the primary objective of the project. The patient sleep position was monitored with a 9 axis MEMS sensor called MPU-9250 (Treffers & Wietmarschen 2016) connected to the main processor NodeMCU ESP32 (ESP32 - ESP-IDF Programming Guide latest documentation', n.d). Three sensors where compared (Table 3.1) for sleep position measurement that included BNO055 by Bosch, L3GD20 by ST and MPU-9250 by Invensense. BNO055 was ranked best from the others but the availability was an issue due to the pandemic. The first BNO055 sensor ordered arrived in a 2 month timeframe and was damaged. MPU-9250 was readily available for shipment within Australia and the properties where ideal for the desired functions and hence were chosen for the project.

Table 3.1: Gyroscope sensor comparison chart

Sensor	Range (dps)	Non Linearity (%)	Sensitivity change vs temperature (%)	Noise density (fps/√Hz)	Zero offset in 250dps (dps)	Rank
BNO055	125-2000	± 0.05	± 0.03		1	1
L3GD20	250-2000	± 0.2	± 2	0.03	10	3
MPU-9250	250-2000	± 0.1	± 4	0.01	5	2

The y axis of the gyroscope sensor was assumed to be the longitudinal axis of the patient to detect sleep postures. The raw gyroscope output presented the rate of change of angle along the y axis which was converted to angle value in degrees. For a patient rotation to the right, increased the angle to the positive quadrant and rotation towards the left, decreased the angle to the negative quadrant. When the patient moves to right lateral decubitus position (RLDP), that is, to the absolute right side sleep the angle approaches positive 90 degrees and for the left lateral decubitus position (LLDP) the angle approaches negative 90 degrees. The supine position is close to zero degrees and the prone position is depicted to be either +180 degrees or – 180 degrees depending on the direction of rotation. The axis of selection and the measurement of the angle of rotation are illustrated in Figure 3.1.

The detection system is strapped around the user's chest and when turned on lying on the supine posture, the device performs a self-calibration to set the zero value of the sensor to start detection. The feedback from the sensor output is given to a mini vibrator that sends vibro-tactile feedback to the user when supine position is detected through the vibration motor to the user's chest. The vibration is delivered to the chest similar to the Buzzpod as it is an ideal position to integrate all system components together and is more comfortable than some PT device positions like neck and forehead. The connection diagram of the sensor and vibrator system is shown in Figure 3.2 and overall working of the proposed model is shown in Figure 3.3.

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Figure 3.1: Orientation of y axis rotation of the sensor for body posture detection (Treffers & Wietmarschen 2016)

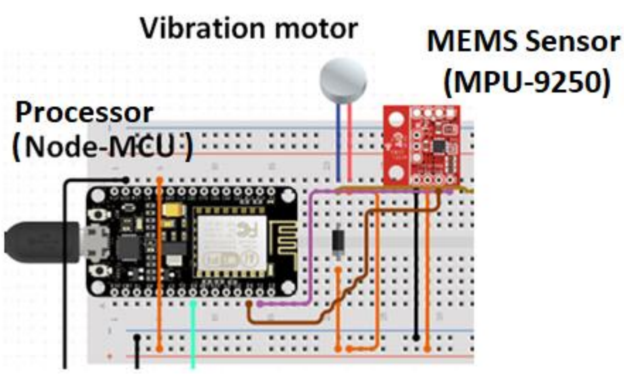

Figure 3.2: Connection diagram for position monitor

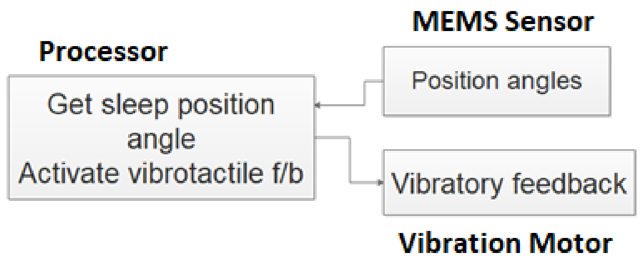

Figure 3.3: Model of position monitoring

The flow chart in Figure 3.4 illustrates the work flow of the position detection process. Once the device is turned ON, an auto calibration is performed to set the zero offset for supine position. After the calibration, the detection loop starts, here the device detects the user position for every second (1Hz) and checks for supine position. The threshold angle for supine position is set to -10 to +10 degrees, so if the value is between these limits the detection is in true state for supine posture. When detection is true, the vibrator pin is activated and a vibro-tactile feedback is delivered to the user and the position is checked again. The loop continues throughout the time of use detecting sleep postures.

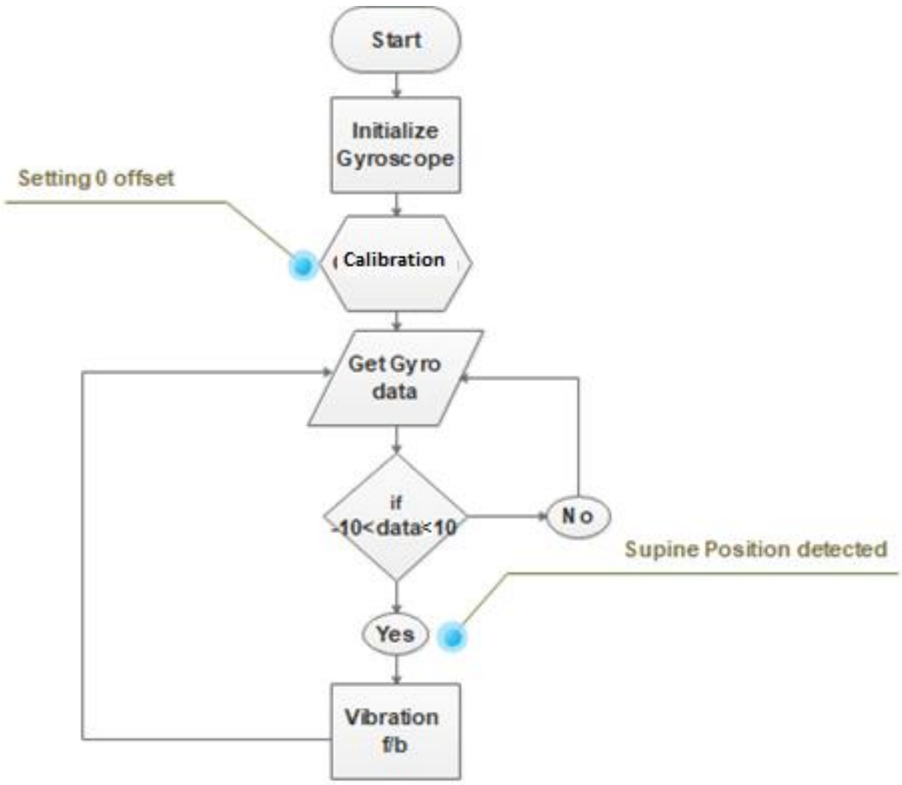

Figure 3.4: Flow chart of position monitoring and detection

3.2. Snore Detection

Snoring frequencies are not constant and vary from patient to patient depending on the degree of upper airway obstruction or sleep positions (Mesquita et al. 2011). So, snoring detection based on threshold frequencies is challenging and pose a lot of limitations including inability to classify between loud and light snoring, sleep environment noises similar to snoring threshold and detection of bed partner snoring. A neural network approach to snoring detection was selected for this project to avoid the limitations posed by the aforementioned noises. It was also evident from Section 2.4 that neural networks approach for snore detection provided considerable accuracy.

The neural network used for this purpose is called as the Tiny Neural Network (TINN) (Louw 2020) that uses a Rectified linear unit (ReLU) activation function to train the network to classify input signals into two groups; active (1) and inactive (0) (Nwankpa et al. 2018). The ReLU activation function is a widely used function which produces linear activation output only in the positive axis and all other values are set to 0 and inactive (Agarap 2019). The active group will be the desired output signal that is the snoring frequencies (in the positive quadrant activating neurons) and the inactive group will be the background noises (0 values leading to inactive neurons). The trained network will be able to score the input signals with a value between 0 and 1, where the undesired signals will be marked closer to 0 and the snoring signals are marked closer to 1. The process of creating the neural network was classified into three phases; Data acquisition (DAQ), Training phase and inference phase. Figure 3.5 provides an overview of the snoring detection algorithm with mentioned phases.

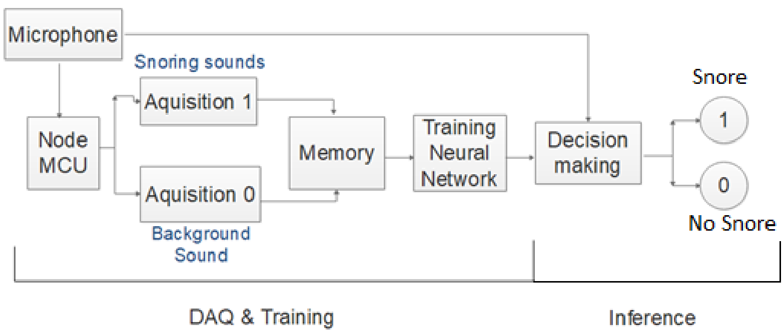

Figure 3.5: Snore detection model

3.2.1. Data Acquisition

This stage of the project aims to collect the snore signals to create datasets for the neural network's learning process. The neural network is required to practice on this input data to create an internal data organization image and to identify the underlying relationships. For this purpose DAQ was performed by acquiring two types of signal; acquisition 1 being the snore signals and acquisition 0 are the undesired environmental signal. The sound signals were collected using a KY-038 microphone sound sensor with inbuilt potentiometer to adjust the threshold-sensitivity of the module (Zen et al. 2020). The sensitivity was set by testing the distance from the snore source and the microphone as mentioned in Section 4.2. The input dataset are stored in the internal file system of ESP32 known as SPIFFS (SPI Flash File System) that stores data in the SPI memory of the processor enabling users to read, write and delete files ('SPIFFS File system - ESP32 - ESP-IDF Programming Guide latest documentation', n.d). The data acquisition to create these input datasets can be performed by two ways: either by uploading existing data from the computer to the SPIFFS through USB port or by performing a simple recording program that allows users to record snoring sounds and background sounds through a simple user interface.

Fast Fourier Transform (FFT) was performed over the signals acquired through the microphone to obtain the frequency components of the input signal and a single sided amplitude spectrum was obtained to extract frequency signals over the positive axis alone to perform frequency threshold comparison and recognition (Settel & Lippe 1994; Cerna & Harvy 2000). Each data acquisition involved the recordings of 3 seconds of snoring signals followed by 3 seconds of background/unwanted signals. The snoring signal frequencies were stored as acquisition 1 signals and the other frequencies were stored as acquisition 0 signals. The FFT parameter was set to 16 frequency bands that is, each recording saves 10 spectra with 16 bands of sound frequencies and one volume data for each of the snoring and unwanted signal acquisition. Meaning, for each acquisition performed a total of 340 data of snoring and non-snoring signals (170 data each) were obtained in one data set. So, for a total of 20 data set acquisitions performed, 6800 data will be produced for the training purpose. The snoring signals passed were of different frequencies and the sleep environmental signals included a mixture of fan sounds, talking, dog barks and other sounds as mentioned in Table 3.2.

Table 3.2: Sound signals included in the acquisition phases

Acquisition	Sound Samples
Acquisition 1 (snore sounds)	Light snoring sounds
	Heavy snoring sounds

	Obstructive snoring sounds
Acquisition 0 (environment noise)	Silent in sleep environment (included fan sound)
	Distant snoring (partner snore signals)
	Conversation audios
	Dog barks
	Random white noise

3.2.2. Training the network

The neural network is trained using the dataset stored in the SPIFFS to enable it to extract snoring sounds from background noises at inference phase. There are three layers in the neural network:

(1) Input layer: Consist of a set of input neurons that represent the features of dataset from the acquisition phase. This layer obtains inputs and passes them to the hidden layer after calculating the activations. Here, the input layers will consist of nodes corresponding to the frequency components obtained from the real time FFT. So there will be 16 input nodes corresponding to the 16 frequency bands produced by the FFT (shown in Figure 3.8).

(2) Hidden layers: These are intermediate layers with a set of neurons with randomly assigned weights that are responsible for acquiring inputs from the previous layer and produce the results by applying the activation functions to the dot product of inputs and weights. They are responsible for creating the relation and decision matrix of the network under training to produce the results for the output layer.

(3) Output layer: Provides the final result from the hidden layers. The output layer here will have a single node that produces a value between 0 and 1 and a value closest to 1 implies a snore signal.

Table 3.3: Training parameters of TiNN for snore detection

Training Parameters	Values assigned
Epochs	6000
Hidden layers	40

Activation function	ReLu
No. of data per epoch	50
Detection threshold	0.95

The different parameters for neural network training is summarised in Table 3.3. The Epochs refers to the iterations of the entire dataset through the learning algorithm and generally, the more the Epochs better the results but more space and time is consumed and each epoch passes 50 datasets. The algorithm creates 40 hidden layers with neurons connected with a ReLU activation function for creating the prediction values. The hidden layers selected is believed to be optimal for this process as it makes the training and prediction process faster and consumes less space while storing the network. The detection threshold determines the value of the prediction above which the signal should be scored as a snore, the predictor values range from 0 to 1 and values closer to 1 predicts snoring, for the final prototype the threshold value was set to 0.95. Different threshold values were investigated for the neural network before finalizing the threshold as discussed in Section 4.3.

During the training phase the network creates the hidden layer for interpolation. The inputs include label 1 with snoring data and label 0 for background data for a supervised learning environment. The network assigns these inputs to random weights and creates the hidden layer for interpolation. The process of learning is an iterative process of forward propagation and back propagation of the data (Yu et al. 2002). In forward propagation, the network is exposed with the training data that spreads throughout the entire network to calculate the labels (predictions). The input is passed in such a way that each neuron applies a transformation to the information obtained from the previous layer and passes them onto the next layer until the data has crossed all the layers and all the neurons have made the calculations. The label predictions for the given data are presented in the final layer. Then, a loss function is calculated to estimate the loss/error in the prediction by measuring the difference from the prediction results with target results. The loss function used for this model is mean squared error calculated as the average squared difference between the observed value (y_o) and the predicted value (y_p) as shown in (1) (Kline 2005).

$$Loss\ function\ (MSE) = -\sum \quad (y \qquad) \text{ -------------- (1)}$$

Ideally, this loss is expected to be zero, so the network adjusts the weight of the interconnection of the neurons until good predictions are obtained. After calculating the loss function, the loss information is sent backwards to all neurons in the hidden layer contributing to the output in back propagation. Depending on the relative contribution of each neuron to the original output, a fraction of the total loss signal is received. The process is repeated over all layers until all neurons have received a corresponding loss signals according to their relative contribution to total loss. The learning process of the proposed neural network is shown in Figure 3.6.

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Figure 3.6: Learning process of the TINN

After back propagation, gradient descent is used to change the weights in small increments by calculating the derivative of the loss function to work out the direction towards global minimum (making the loss as close to zero as possible) (Yu et al. 2002).

3.2.3. Inference phase

This is the final phase of the neural network where the system listens to the input audio signals and tries to detect snoring signal patterns from the surrounding sounds. The audio signals from the microphone undergo FFT and the frequency components after the process will be the inputs to the neural network as depicted in Figure 3.7. The inputs are passed onto the trained hidden layers of the neural network. The input passes through all the neurons in the hidden layer with adjust weights for prediction as shown in Figure 3.8.

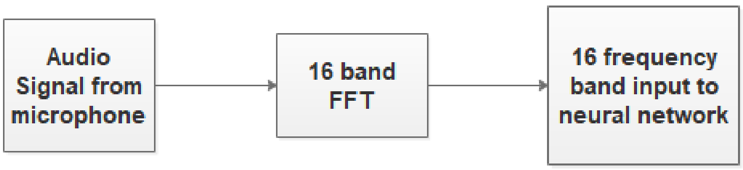

Figure 3.7: Pre-processing audio signal before input to NN

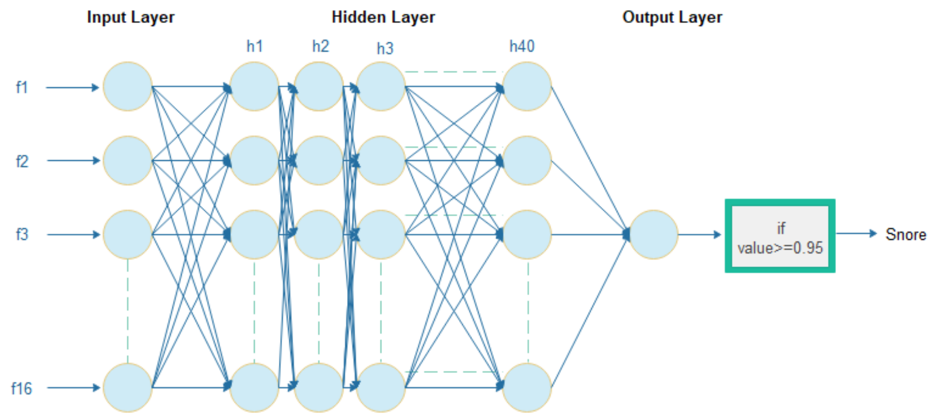

Figure 3.8: Proposed NN model for snore detection

For a snore signal, maximum number of neurons are activated as the snore signal weight matches the prediction weight and the activation function produces an output close to maxima (1). More the neuron links activated, more the weight and the result will have a value close to 1 and as per our detection threshold, any value greater than 0.95 is a snore detection that triggers a vibratory feedback through the vibrator. For a non-snoring signal, the network weightage will be close to minima (0). The signal fails to trigger the activation function and fine number of neurons are activated. The result approaches a value closer to 0 and less than the detection threshold, implying no snoring detection and the detection continues. The inference phase is summarised along with the training phase in Figure 3.9.

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Figure 3.9: Summary of snore detection process

3.3. Data Logging

The audio signals from the microphone are stored by the prototype for sleep scorers to analyse snoring events and frequencies offline. This feature allows real time data logging of physiological signals that allows a doctor or a sleep scorer to study the patient sleep quality and determine patient snoring severity and also for the diagnosis of possible sleep related diseases. A micro SD breakout board is connected to the processor and the microphone to store the analog signals as shown in Figure 3.10.

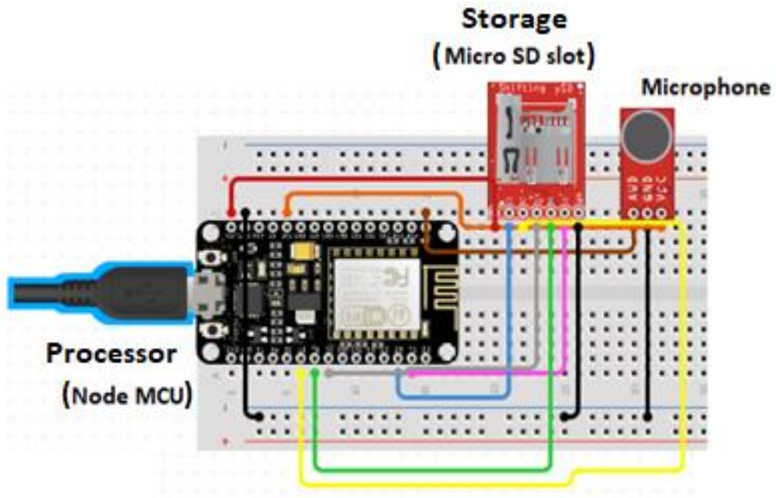


Figure 3.10: Data logging model

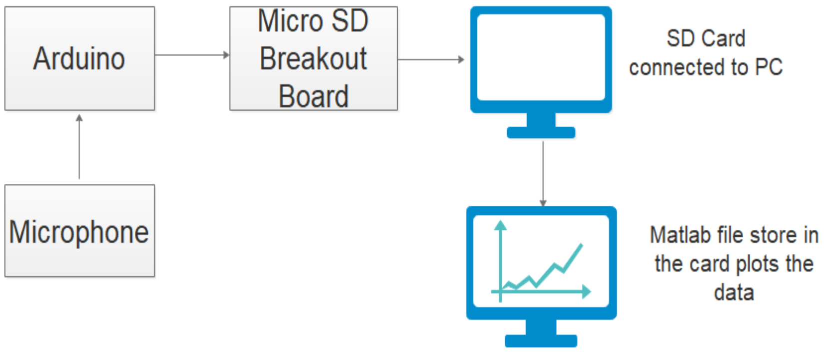


Figure 3.11: Work flow for data logging

A text file is created in the storage card to which the raw signal data are saved to (shown in Figure 3.11). The audio signals are stored in the form of integers in a column of data. The data from the test can be plotted across time to get an interpretation of snoring signals over the time of use. Matlab software was used to produce the plot shown in Figure 3.10 of the audio signal from the raw data.

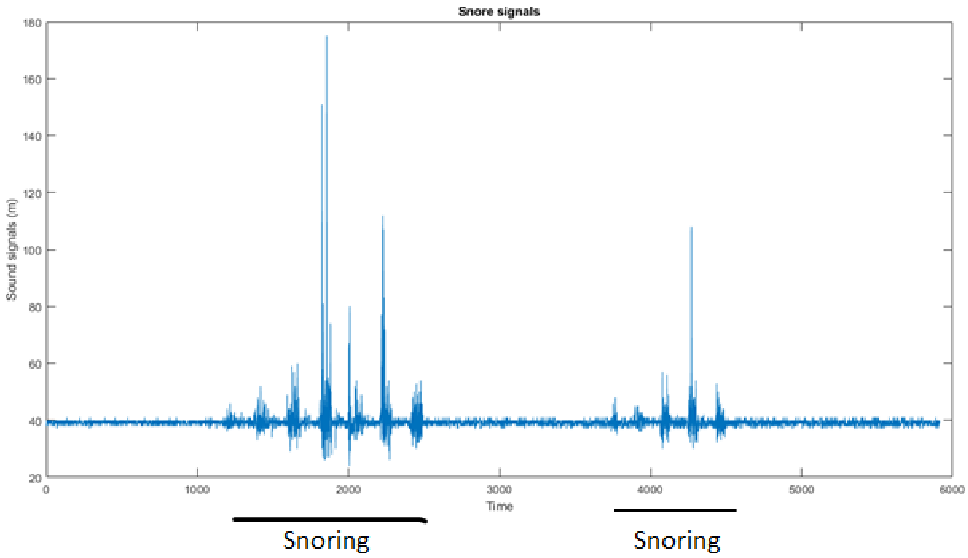


Figure 3.12: Data logging of snore signals for offline analysis

3.4. Final Prototype

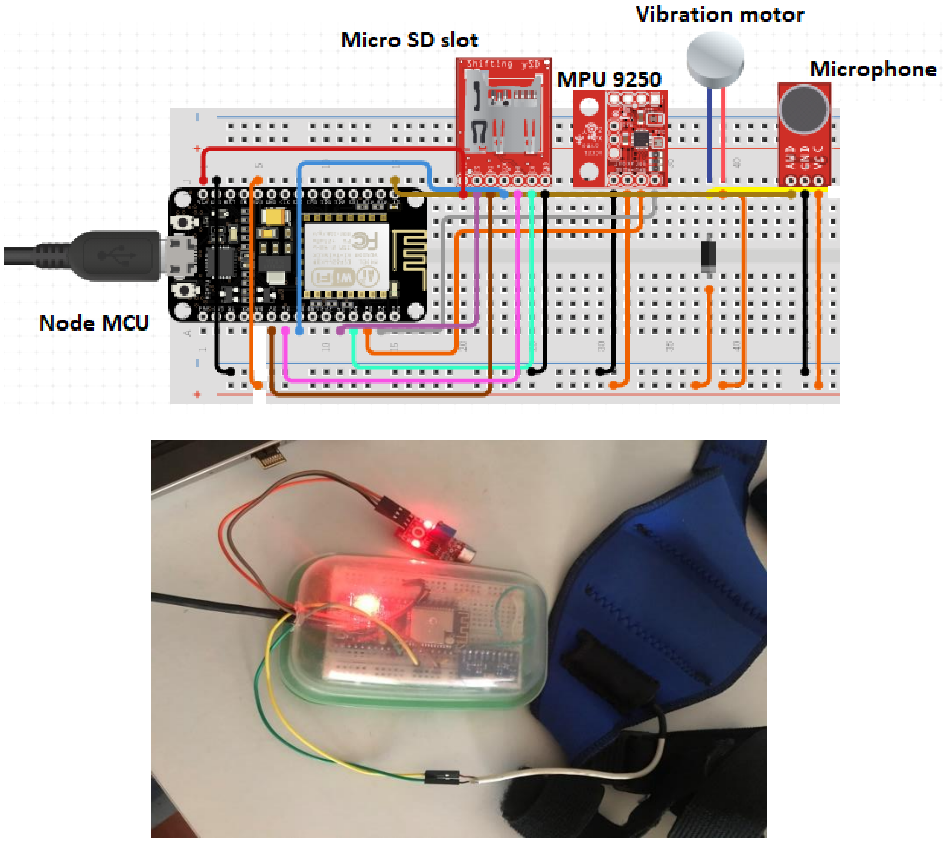


Figure 3.13: Final prototype model (top) and PT device developed

The final prototype (shown in Figure 3.13) integrates the models described in sections 3.1, 3.2 and 3.3 to present a smart supine avoidance alarm system with snore detection and data logging. The device when turned on calibrates the gyroscope for zero offset and starts both position and snoring detection. For the supine avoidance alarm, the device detects the patient sleeping position from the gyroscope angle output and sends a vibro-tactile feedback to the user as an alarm. It then waits for the patient to shift posture, if the patient does not change the position after the vibration, the device waits for a snore detection as a threat for OSA. On detecting a snore in the supine position, the device delivers continuous vibratory feedback until the user avoids the supine sleep posture. In addition to this detection and alarm process, data logging of the audio signal is carried out through a micro SD storage device throughout the time of use. This storage of data allows plotting the snoring data of the user to identify the significance of their snoring frequencies and the intervals of snoring throughout the night. In addition, the detection logs for snoring with time stamps are provided by the device to distinguish snore signals with other noises in the audio plot obtained from the logger.

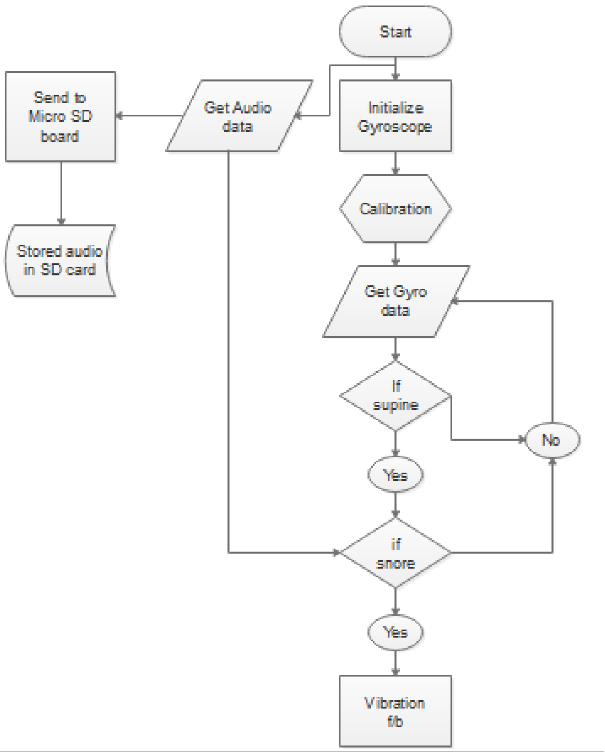


Figure 3.14: Flow chart of the final prototype for snore detection and supine avoidance

The device can also be operated as a standalone snoring avoidance system by bypassing the position monitor and allowing it to alarm users when snore detection is carried out irrespective of the sleep position of the patient. That is, when the user starts snoring, the device detects the snore and sends the vibro-tactile alarm for the user to avoid snoring. This would allow the user to reduce their snoring events in sleep and also possibly train the brain to avoid potential snoring positions in sleep.

Chapter 4: Results and Discussion:

This section involves the discussions on the test methods and the observations obtained from them for different algorithms. Finally, the test results were used to compare the accuracy, sensitivity and specificity of the proposed snoring detection model with the previous models in the literature and also successfully compared the proposed PT device with the previous models.

4.1. Testing the position monitoring algorithm

Sleep position monitoring is the primary objective of this project. The raw gyroscope, accelerometer and magnetometer data from the sensor was obtained initially and tested to draw conclusion on the change in the values under different positions of the sensor. The gyroscope value helped in measuring the rate of change of angle along an axis and was found more appropriate for this algorithm. The y axis of operation of sensor was assumed as the body axis and used to calculate the rate of change of angle along the axis.

However, the raw gyroscope data seemed inconclusive, so a program was added to calculate the angle of rotation. This would allow the system to assign angle values (in degrees) to sleep positions, ideally the aim was to set absolute 0 degrees to the supine position and angle added to positive quadrant for right turn and angle added to the negative quadrant for left turn. The initial test of this model worked according to the defined process and angle values were obtained as expected. But, it was noted that output did not start from exact zero for supine posture according to the defined algorithm. For this function a calibration program was added to the main code that calculates the zero offset of the sensor and cancels it out before the start of the program. The angle values upon rotation of the sensor were obtained as expected and the observations are shown Table 4.1.

Table 4.1: Sleep positions and angles measured by the prototype

Sleep position	Position angle (degrees)
Supine sleep position	0^o
Right Lateral Decubitus Position (RLDP)	$+90^o$
Left Lateral Decubitus Position (LLDP)	$- 90^o$
Prone Sleep Position	$\pm 180^o$, sign depends on the direction of rotation to reach the position

.

4.2. Testing sound sensors for snoring sound acquisition

The snore signals were acquired as sound signals from a microphone. Two Arduino adaptable microphones were tested for the sound acquisition. The microphones selected for testing were Electret microphone breakout board and KY 038 sound sensor module as shown in Figure 4.1. The Electret break out board is an arduino adaptable module that couples a microphone (100Hz – 10kHz) with a 60x rail-rail precision amplifier (OPA344) that amplifies the sound detected from the input. The latter, is a sound sensing module that has an inbuilt sensitivity regulator that allows user to adjust the amplification of the sound according to the design requirements.

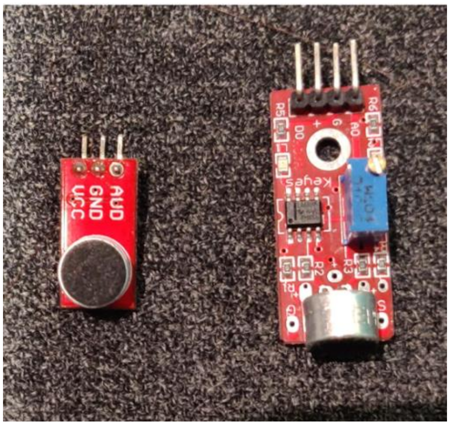


Figure 4.1: Electret microphone breakout board (left); KY038 sound sensor (right)

The microphone break out board was tested first for sound acquisition. A software was used to read an analog pin of an arduino to produce a real time plot of the input data to plot the microphone output. The amplitude plot of the breakout board is shown in Figure 4.2.

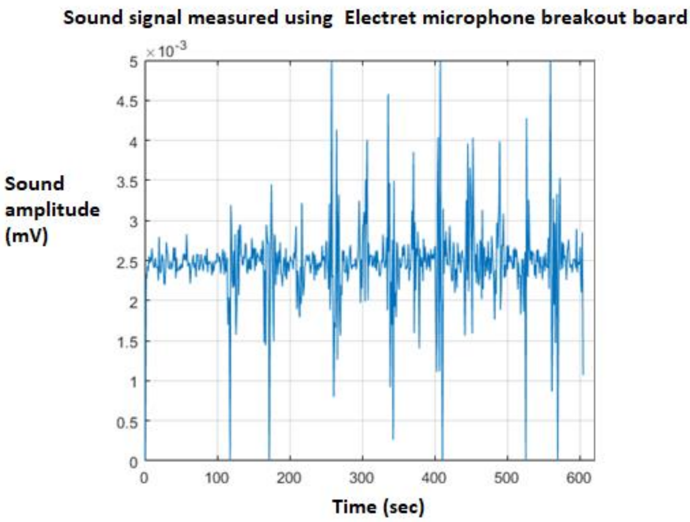


Figure 4.2: Snore signal from microphone breakout board

The microphone was able to clearly obtain snore signals and also amplified the same for signal acquisition but the raw data plot seems to be noisy and inappropriate. Since the amplification in the board is fixed and very high, the noises generated in the environment also seemed to amplify. This is not ideal as an amplified noise can be hard to filter out and can affect the snore detection algorithm that aims to classify snore signals from noises based on the frequency patterns.

The KY038 sound module was selected to overcome this issue, since the sensitivity of the module can be calibrated by the user that can help to achieve a desired amplification level. The sensitivity was manually adjusted while plotting the data until the desired output was obtained. The sound module was able to acquire amplified snore signals successfully with limited interference from noises as evident from the plot in Figure 4.3. This module with the selected sensitivity was used for the snore signal acquisition.

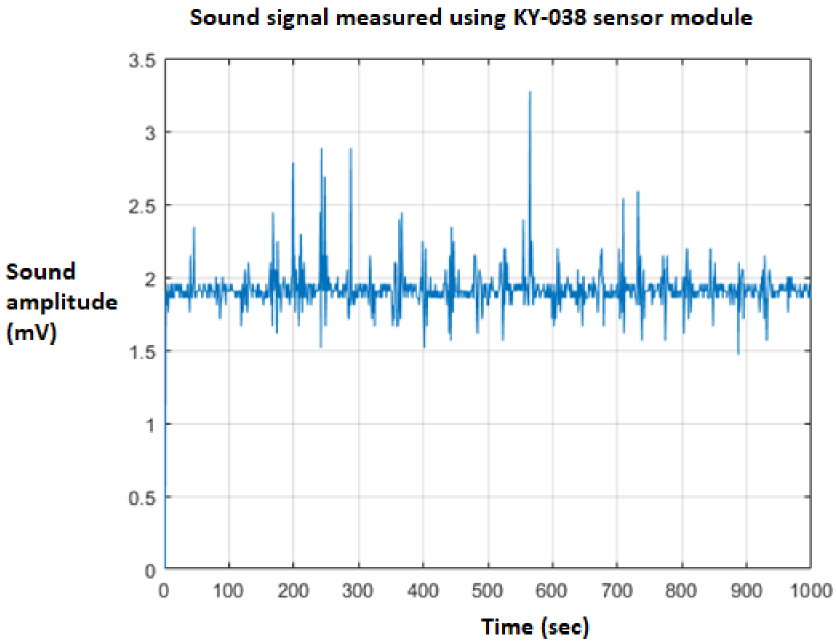


Figure 4.3: Snore signal from sound module with selected sensitivity

The raw data from the module alone is insufficient for the detection model because the raw signals can be large which makes the neural network process complex and pose a significant threat to increase the errors in detection cycle, instead a feature extraction pre-processing of the signal to isolate frequency components can be an ideal choice (Abeßer 2020). The signal required some pre-processing to extract frequencies from the spectrum as the snore detection algorithm is trained to isolate snoring frequencies from other background frequencies. A Fast Fourier transform (FFT) was used to perform this function. FFT allows to separate frequency samples from the input signals and it also produces a single sided amplitude spectrum (shown in Figure 4.6) that allows the system to extract all the peaks from the positive quadrant. This signal processing method allow to improve the efficacy of the snore detection algorithm and also makes the process simpler as training a NN based on a raw sound signal can be laborious and prone to additional noises.

4.3. Method for testing the snoring detection model

The prototype was rigorously tested to find the right parameters for snoring detection. The tests were conducted in a sound proofed sleep lab at the Adelaide Institute of Sleep Health (shown in Figure 4.4) to identify the accuracy, sensitivity and specificity (observed in section 4.3.4) of the snore detection using the number of true/false positives and negatives. The true positive in this case was snore detection from the prototype while presented only to snore sounds leading to a true detection and a vibratory feedback. True negative is the scenario when the device did not detect any snore sounds when subject to non- snoring frequencies and provided no vibrational feedback. False positive will be the case were the device provides wrong snore detection for snoring when presented with non- snoring frequencies and provides an unwanted vibrational feedback. The False negative for the system would be the failure of the device to not be able to detect any snoring when presented with snoring sounds. The summary of the true/false positives and conditions are given in Table 4.2.

Figure 4.4: Sound proofed sleep lab at AISH

Table 4.2: True/false positives and negatives of snore detection

Conditions	Scenario	Detection	Outcome
True Positive	Snoring	Yes	Detection and alarm
False Positive	No snoring	Yes	Wrong detection and alarm
True Negative	No snoring	No	No detection and no alarm
False negative	Snoring	No	No detection and no alarm

The expected test results should be satisfying the true positives and negatives and avoiding the false positive and negatives as much as much as possible. The device detection threshold and input training data were changed while testing the prototype to satisfy this condition, while the other network parameters were kept constant. The study was conducted by playing snoring sounds and possible sleep environment sounds randomly in the background. The sleep environment sounds consisted of silence (no snoring or any sounds), dog barks, fan sounds, conversations, distant snoring (mimics partner snore) and random white noises. The test were conducted on different stages with different parameters of snoring detection and simultaneously recorded by a PSG snore and audio detector (as shown in Figure 4.5) that was compared with the device detection to understand the true/false positives and negatives. The scoring of the detection was performed by a trained scorer in the sleep lab for all the test runs.

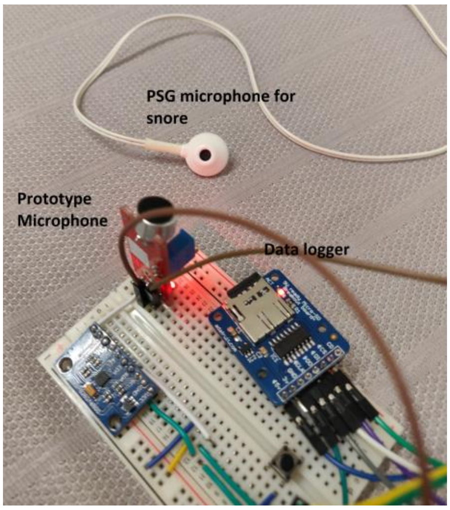


Figure 4.5: Setup for testing the snore detection algorithm

OBSERVATIONS:

4.3.1. Test I: Initial Snore test with selected parameters

The primary test was conducted on the prototype that was trained with 10 input datasets that included only 3400 sound frequency data of snore sounds and silence alone (1700 data each). The detection threshold was set to 0.9 and the tests were conducted and the test parameters are summarized in Table 4.3.

Table 4.3: Test 1 parameters

Input Snoring data	1700 frequency samples
Input silent environment data	1700 frequency samples
Detection Threshold	0.9

The test was conducted over a span of 6 minutes in which the prototype was presented with 3 minutes of snoring sound and 3 minutes of silence, that produced a total of 35 detections. The snoring detections with respect to the sound cycles were recorded and observed as in Table 4.4.

Table 4.4: Test 1 observations

Sounds	Duration (seconds)	Detection cycle (per 3 seconds)	Detections
Snoring	180	60	24 true detections
Silence	180	60	11 false detections

The results were not satisfying as only 24 true detections were observed out of the 60 detection cycles which is significantly low and although the test only presented 11 false detections, it is not a satisfactory result. This could be because of the insufficient amount of input data sets and probably a higher threshold for the limited input training data resulted in lower true detections. The summary of true/false positives and negatives of the first test is illustrated in the Table 4.5.

Table 4.5: Summary of true/false detections in Test I

True positive Expected: 60 snore detections in snoring cycle TP = 24	**False positive** To avoid: 60 false detections in non-snoring cycle FP = 11
False negative To avoid: 0 detections in snoring cycle FN = 36	**True negative** Expected: 0 detections in non-snoring cycle TN = 49

The test produced considerable snore detection over the time period but was still identified as low for the prototype model and the number of false detection in the non-snoring period was observed to be high as well. This result could be due to the limited amount of input dataset and the insufficient detection may be caused due to a large signal threshold. The next test aims to improve on this shortcoming by adjusting the training parameters.

4.3.2 Test II: Increasing input training sample and reducing threshold

The input datasets where increased to 15 that included a total of 5100 training data (2550 data each of snoring and silence alone). The detection threshold was dropped to 0.85 to possibly increase the counts of true snoring detections.

Table 4.6: Test 2 parameters

Input Snoring data	2550 frequency samples
Input silent environment data	2550 frequency samples
Detection Threshold	0.85

The test was conducted with similar conditions to primary test, with 3 minutes of snoring and 3 minutes of non-snoring events. But the non-snoring events included other possible sleep environment noises as mentioned before. A total of 53 detections were obtained from the test and the snoring detections with respect to the sound cycles were recorded and observed as in Table 4.7.

Table 4.7: Test 2 observations

Sounds	Duration (seconds)	Detection cycle (per 3 seconds)	Detections
Snoring	180	60	37 true detections
Silence	60	20	4 false detections
Dog bark	30	10	5 false detection
Distant snore	30	10	7 false detection
Conversation	30	10	3 false detection
White noise	30	10	3 false detection

The observed results showed an increase in true detection counts by reducing the threshold and increasing the input dataset. However, the number of false detections also increased to 22 detections. This could be due to the reduction in threshold as the random sounds introduced to the system were not included in the training datasets. The summary of true/false positives and negatives of the second test is demonstrated in Table 4.8.

Table 4.8: Summary of true/false detections in Test II

True positive Expected: 60 snore detections in snoring cycle TP = 37	**False positive** To avoid: 60 false detections in non-snoring cycle FP = 22
False negative To avoid: 0 detections in snoring cycle FN = 23	**True negative** Expected: 0 detections in non-snoring cycle TN = 38

Reducing the threshold helped in increasing the number of snore detections but also managed to significantly increase the amount of false detections. The lack of noise signal frequencies in the learning algorithm can also be the reason for increasing the false detections. The training datasets for the next test involved the noise signals mentioned here and also the number of datasets were increased.

4.3.3. Test III: Increasing training samples and detection ratio for model efficacy

The input dataset was again increased to 20 datasets with a total of 6400 training data (3200 snoring frequencies and 3200 non-snoring frequencies). The non-snoring frequencies included samples of silence, distant snore, dog barks, conversation and white noises. The detection threshold was set back to 0.9. Table 4.9 lists the test parameters of Test III for improving the detection algorithm.

Table 4.9: Test 3 parameters

Input Snoring data	3200 frequency samples
Input silent environment data	3200 frequency samples
Detection Threshold	0.9

The snore model was again tested with 3 minutes of snoring and 3 minutes of other non-snoring sounds similar to the previous tests. A total of 55 detections were obtained from the test and summarized in Table 4.10.

Table 4.10: Test 3 observations

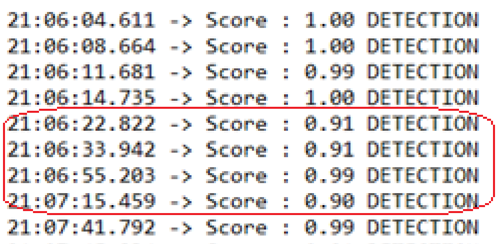
Sounds	Duration (seconds)	Detection cycle (per 3 seconds)	Detections
Snoring	180	60	45 true detections
Silence	60	20	4 false detections
Dog bark	30	10	2 false detection
Distant snore	30	10	2 false detection
Conversation	30	10	1 false detection
White noise	30	10	1 false detection

The system provided improved results for the new test parameters, the number of true detections increased by 8 and the number of false detections decreased to only 10 detections over 60 detection cycles as shown in Table 4.11.

Table 4.11: Summary of true/false detections in Test III

True positive Expected: 60 snore detections in snoring cycle TP = 45	**False positive** To avoid: 60 false detections in non-snoring cycle FP = 10
False negative To avoid: 0 detections in snoring cycle FN = 15	**True negative** Expected: 0 detections in non-snoring cycle TN = 50

The test results show significant improvement in the detection algorithm. However, the number of false detection can still be reduced. On carefully analysing the snore detection log of the device shown in Figure 4.6, it was found out that almost all of the snore signals had a threshold greater than 0.95 and almost all the non-snoring signals providing the false detection had a threshold between 0.9 and 0.95 as evident in the Figure 4.6.



```
21:06:04.611 -> Score : 1.00 DETECTION
21:06:08.664 -> Score : 1.00 DETECTION
21:06:11.681 -> Score : 0.99 DETECTION
21:06:14.735 -> Score : 1.00 DETECTION
21:06:22.822 -> Score : 0.91 DETECTION
21:06:33.942 -> Score : 0.91 DETECTION
21:06:55.203 -> Score : 0.99 DETECTION
21:07:15.459 -> Score : 0.90 DETECTION
21:07:41.792 -> Score : 0.99 DETECTION
```

Figure 4.6: Detection log showing non-snoring detections with values less than 0.95 detection threshold

So, by increasing the training data set and the system threshold the number of false detections is expected to reduce.

4.3.4. Test IV: Final test with desired learning parameters for model efficacy

The detection threshold of the neural network was changed to 0.95 as a result of the evaluation of the detection log from the previous test. The increase in detection threshold should help avoid most of the non-snoring frequencies observed in previous test without significantly effecting the snore detections. All the other parameters were left unchanged for the test and the previously trained network saved in the device memory was again used for this study. The network parameters for the final test are listed in Table 4.12.

Table 4.12: Test 4 parameters

Input Snoring data	3200 frequency samples
Input silent environment data	3200 frequency samples
Detection Threshold	0.95

The test produced 78 detections over 10 minutes of testing. This included 5 minutes of snore signals and 5 minutes of other signals included in the tests before. The summary of all the detections are tabulated in Table 4.13.

Table 4.13: Test 4 observations

Sounds	**Duration (seconds)**	**Detection cycle (per 3 seconds)**	**Detections**
Snoring	300	100	74 true detections
Silence	90	30	0 false detections
Dog bark	60	20	1 false detection
Distant snore	60	20	2 false detection
Conversation	60	20	0 false detection
White noise	30	10	1 false detection

The observations showed significantly improved snoring detection. There were 74 true detections recorded over 5 minutes of snoring signals (100 detection cycles). The test only produced 5 false detections from 100 detection cycle in the non-snoring event as evident from Table 4.14.

Table 4.14: Summary of true/false detections in Test IV

True positive Expected: 100 snore detections in snoring cycle TP: 74	**False positive** To avoid: 100 false detections in non-snoring cycle FP: 5
False negative To avoid: 0 detections in snoring cycle FN: 26	**True negative** Expected: 0 detections in non-snoring cycle TN : 95

The results observed from this test showed an improvement in accuracy for snoring detection for the proposed project goal. The above trained neural network is used for snore detection in the main project algorithm.

All the test results are summarized in Figure 4.7 and the improvement of detection over test is evident from the graph. It is also evident that as the number of input datasets increased the number of true detection increased with it. The final test produced significant percentage of true detection while having a relatively low number of false detection even though the test was carried out for a longer period of time. The accuracy, sensitivity and specificity was calculated for all tests to measure the success of the snoring detection algorithm and the observations were recorded in Table 4.15.

Table 4.15: Accuracy, Sensitivity and Specificity of all tests

Tests	Accuracy	Sensitivity	Specificity
Test I	0.61	0.68	0.81
Test II	0.62	0.61	0.63
Test III	0.81	0.75	0.83
Test IV	0.84	0.74	0.95

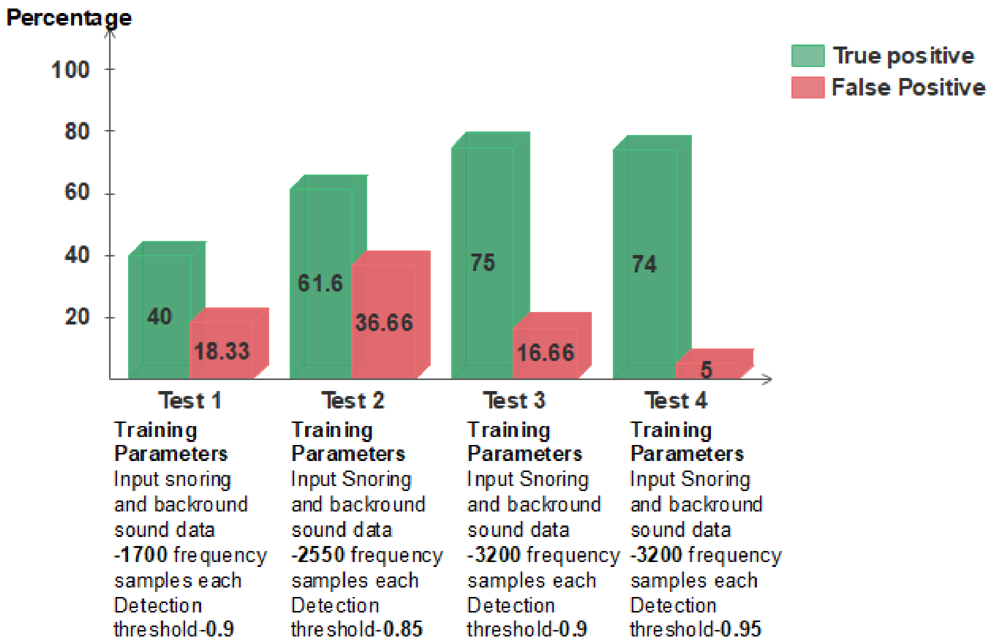


Figure 4.7: Summary of test results of snore model

The final test produced considerably better accuracy and specificity, although the sensitivity for the test is slightly low. The proposed snore detection model was compared with previous models by comparing Table 4.15 with Table 2.3 from section 2.4 to measure the success of the algorithm. The specificity of the model is in the same range of most of the previously reported models and in some it is better. The accuracy and sensitivity of the system is notably low compared to the other models, this could be because of the simpler neural network used for this process compared to the complex deep learning algorithm used by the others. The use of such complex neural network was limited for this project because of the limited knowledge of building them and the inability to store the complex networks due to low storage space of the processor. Most of the previous models were based on a mobile application that uses mobile storage and inbuilt functions for sound recording and processing that is advantageous compared to the proposed model that includes an integrated signal acquisition and processing method. More limitations subjected to the project is mentioned in Section 4.5.

4.4. Testing the final prototype:

The final prototype was presented by integrating the snoring detection model with the position monitoring algorithm. A controlled trial of the prototype was performed where the device was strapped on a user and the final algorithm was tested with controlled snoring sounds played randomly in different sleep positions. The user was asked to notify every vibration delivered from the system that was recorded with the corresponding time separately.

Figure 4.8: Testing the prototype

The recorded user detections where compared with the detection logs from the prototype to draw conclusion from the test to measure the success of the prototype. The prototype produced vibrations immediately when supine posture was detected as defined by the algorithm. It was also found that the snoring detections were carried out in supine position as required by the algorithm. However, there were a few detections observed while changing the position or immediately after changing the position from supine posture. This could be due to the 3 second delay between the detections in the algorithm. The observation from this test is listed in Table 4.16.

Table 4.16: Final test observations

Sleep Position	Snore interval	Snore detection	Vibration feedback
Supine	2 min	Active : 17 detections	17 alarms
RLDP	1 min	Inactive: 0 detections	1 alarm while turning
LLDP	1 min	Inactive : 0 detection	1 alarm while turning
Prone	1 min	Inactive : 0 detection	0 feedback

The snore detection algorithm was tested on all position of sleep and the results showed desired outputs. The detections on supine RLDP and LLDP were not interfered and a proper log was obtained. However, the detection count in prone position was significantly low compared to other positions. This could be due to microphone failing to get the sound signals effectively as it is covered under the body. Since prone position does not produce significant snoring and is safe from OSA, the snore detection in this position is less required.

The designed prototype is a relatively simpler and comfortable approach compared to CPAP or other therapy methods. This prototype is novel as it aims to be smarter by incorporating the detection of sleep parameter (snoring) that can be used to detect OSA episodes beforehand. Unlike previous models that aim to perform supine avoidance irrespective of any apnoeic events like the PT devices mentioned in Section 2.2, this device aims to detect events before alarming the user that would reduce the nuisance alarms which was a leading cause for limited patient adherence for positional therapy.

The data logging feature of the proposed model will allow clinical studies to be more convenient and time saving. The patient need not undergo an overnight sleep study in a sleep lab to monitor and assess their sleep health, instead the data logged by the device can be used by the sleep doctor or scorer to assess the patient's sleep health.

4.5. Limitations:

The prototype testing was over a limited time compared to the actual overnight usage. So, the test results are limited to data for effective conclusions although they prove considerable algorithm success. More tests are required to understand the clinical potential of this project in treating OSA. The system accuracy can be improved by the integration of advanced signal processing methods to extract user snore signals from all potential noises including bed partner snoring in the acquisition phase. A more developed neural network algorithm with high end deep learning mechanism can be used to improve the system accuracy and sensitivity.

Insufficient pins in the NodeMCU processor limit the integration of more sensors for future use and also these plugin Arduino modules make the prototype comparatively bulky. To avoid this, system optimization is required by possibly fabricating a System on Chip (SOC) or Embedded Systems manufacturing that can be used to substitute the entire prototype into a work board to get an optimized product. The absence of a real time clock (RTC) in the Micro SD breakout module limits the storage of real time to plot with the snore signals.

The sleep comfort for the users is still to be measured because a bulky prototype can be uncomfortable and may sometimes obstruct users from moving to a prone position that could lead to an unwanted arousal. In the prone position, the snoring detection did not function properly as the microphone was under the body, so microphone placement should be considered.

Moreover, the snoring detection algorithm may not be able to differentiate user snoring with bed partner snoring. A relatively high frequency snoring from a bed partner can cause false detections and nuisance alarms which can be a major challenge.

Chapter 7: Conclusion and Future Directions

Three major algorithms: position monitoring, snore detection and data logging; were proposed for the development of a smart supine avoidance alarm device. All three algorithms were tested to identify the best system parameters for function before integrated to produce the final prototype. The snore detection algorithm was a major objective of the thesis and was tested with different parameters in a sleep laboratory and the model was validated. The detection algorithm carried out 74% true detections and only produced 5% of false detections (only 5 detections from a 100 events) on the final test that supports the use case of the algorithm. The accuracy sensitivity and specificity of the model was calculated to be 0.84, 0.74 and 0.94 respectively. Once the algorithms were validated, the final prototype was produced by integrating all three algorithms and tested for accuracy. The test results validated the proposed model and the observations showed an accurate supine avoidance device that produced smart alarms when snoring is detected in the supine position.

Future Directions:

The addition of other parameter detections like the use of thoracic band for measuring respiratory rate, use of saturation probe to measure oxygen saturation in sleep and other sleep parameters in PSG studies can play an important role in PT. This could also lead to the development of close to all-in-one sleep monitoring device that can perform sleep positioning and remote monitor vital PSG parameters that could be used to treat other sleep disorders as well. Also, the correlation of apnoea with respiratory parameters will lead to an accurate therapy method as apnoea events are mostly followed by irregular breathing patterns and declining oxygen saturation.

A new deep learning algorithm can be developed to substitute the algorithm used for this thesis that can improve the detections even better. The challenges from bed partner snoring can be overcome by the use of advanced signal processing methodologies like blind source separation (Choi et al. 2004) which can allow a model to separate user snore signals specifically from a cluster of signals allowing the detection algorithm to be user specific and avoid bed partner snoring or any other environmental noises.

Thought on integrating IoT or cloud based data monitoring was considered, this would allow access of user data remotely allowing the doctors or sleep clinics to access data easily for studies avoiding a laborious process of examinations. This in turn increases the patient adherence to this therapy. IoT integration is possible with the given project as the processor involved includes an inbuilt WiFi module that allows real time data transmission and receiving capabilities. However, an advanced processor and communication technique with high speed and long range data transfer like the LoRa (Long Range) protocol by Semtech will be a much suitable option as it is based on a low-power-wide-area network that fits the duration of use of the device and a durable network connectivity compared to the Node MCU used in this project.

Developing an integrated system with all components is necessary to achieve device success. This allows optimization of the device avoiding bulkiness for user comfort and also reduces the cost of assembling such a device. An integrated system can also be battery powered and rechargeable, making the device more user-friendly.

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