

VALIDATION OF NOISE LEVEL IN OMU-ARAN TOWNSHIP USING ARTIFICIAL NEURAL NETWORK

BY

OLAJIDE, OPEYEMI SUNDAY

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# DECLARATION

I, OLAJIDE OPEYEMI SUNDAY, an M.Eng student from the ***Department of Civil Engineering***, Landmark University, Omu-Aran, hereby declare that this thesis entitled ***“Validation of Noise Level of Omu-Aran Township using Artificial Neural Network”***, submitted by me is based on my original work. Any material(s) obtained from other sources or work done by any other persons or institutions have been duly acknowledged.

**--------------------------------------------------------**

Student’s Full Name and Matriculation Number

**----------------------------------------------**

Signature & Date

# CERTIFICATION

This is to verify that the thesis has been read and accepted by the Department of Civil Engineering, Landmark University, Omu-Aran, Nigeria, as meeting the requirements for the M.Eng. degree (Civil Engineering).

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Dr. O.O ELEMILE Date

(Supervisor)

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Dr. J.A Gana Date

(Co-Supervisor)

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Dr. J.A Gana Date

(Head of Department)

# DEDICATION

I dedictate this thesis to Almighty God for His great grace, mercy, love, protection and provision in making this programme a successful one , and to the entire family of Olajide and Osatuyi.

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All thanks to God, for life, wisdom, and strength given in order to make this thesis a yielded result despite all challenges. I glorify the name of the Lord for providing beyond expectation in making this dream a reality.

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# ABSTRACT

The inconspicuous nature of noise pollution has made it undetectable in both developed and developing countries with associated health complications. In Nigeria, several studies have suggested different models to mitigate noise pollution, but there is none carried out on noise levels in Omu-Aran, therefore this study, was aimed at validating noise levels in Omu-Aran Nigeria using Artificial Neural Network.

A sound level meter type SL4010 was used to measure, the noise levels in the morning, afternoon, and evening daily for the duration of three weeks from three zones. The zones are subdivided into seven locations namely: Oke-Agbede, Landmark junction, High Court junction, Latinwo Market, Ile-Nla, Falaye, Landmark Chapel, Central Market, Central Roundabout, Iganngu/Okeki, Ile-Olupo/Ile-Adee, Odo-Areyin, Egbe Garage, Otolorin/Federal Hospital Junction, GRA, Agamo, Taissa Junction, Bovas, Orolodo/Olomu Palace, Secretariat/Eco Bank, and Taiwo. Health risk assessment was evaluated using the recommended exposure limit (REL) and permissible exposure limit (PEL) established by the National Institute of Occupational Safety and Health while Artificial Neural Network was used to validate the noise levels. Descriptive statistics were used to manage the data at P< O.05 level of statistical significance

The average mean noise levels for all locations were 67.82± 2.1, 68.7± 1.87, and 69.53± 2.24 dB for the mornings, afternoons and evenings respectively. There was a significant difference in noise levels across the period of the day where Central Roundabout, Central Market, and Landmark University Chapel were exposed to non-permissible noise levels of 87.24, 86.78, and 83.16 dB respectively. The noise level exposure at each location has health issues ranging from discomfort to cardiovascular effects, and an increase in physiological responses with a noise level of 60dB to 87.24 dB. The ANN model validated the noise levels in Omu-Aran township as one of the best results with 21 associated input features which showed high performance of 97.84% accuracy and the root means square error to be RMSE =0.1096.

Population and human activities have an impact on the noise levels at the different locations in Omu-Aran with its health-related issues. Hence, there is a need for law enforcement at the local level to mitigate the health-related issues

**Key Words**: Noise Levels, Health Risk Assessment, Artificial Neural Networks, Omu-Aran

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# LIST OF ABBREVIATION

OSHA-Occupatonal Safety and Health Authority

WHO-World Health Organization

NIOSH-National Institute of Occupational Safety and Health

PEL-Permissible Exposure Limit

REL-Recommended Exposure Limit

dB-Decibel

TWA- Time-Weighted Average

ANN-Artificial Neural Network

RMSE- Root Mean Square Error

MLP-Multilayer perceptron

# CHAPTER ONE



## 1.0 INTRODUCTION

## 1.1 Background of the Study

The anomaly of pressure variation that the human ear can perceive over time is denoted to as noise, which had been tagged harmful to public health and had devalued the quality of life enjoyed especially in urban areas (Münzel *et al*., 2020). Both developed and developing countries experience environmental threats from high noise level exposure. This is due to consistent migration from rural to urban areas, and illegal location and activities formation of both formal and informal industries (Mehdi *et al*., 2011). For example, a large percentage of people will love to be mobile with vehicles rather than walking or cycling. Also, commercial and industrial activities make use of electricity generators and, entertainment activities within the streets that are not timely or legally constrained, therefore leaving most cities and towns noisy (Vaccari *et.al.,* 2019). Unplanned urbanization, poor transportation network development, a growth in motor cars, pervasive technology, and mechanized advancement all contribute to noise pollution concerns in densely populated residential areas. Noise pollution in cities is mostly triggered by traffic, industry, construction, and other activitie (Cueto *et al*., 2017). Numerous studies have found that chronic noise exposure is not only known to impairs human ear impariement but also raises blood pressure, heart illness, nervousness, and sleeplessness (Munzel *et al.*, 2017). Thus, noise contact had led to an increase in drug usage and a constant visitation of people that are affected to hospitals (Farooqi *et al*., 2017).

In 1972, the World Health Organization (WHO) agreed to designate noise as a form of pollution, and the first global study on the subject was conducted in 1972.The Stockholm Conference designated noise as a distinct pollutant seven years later, in 1979. Later, a research published in 1990 identified Spain as the country with the world's second-highest rate of noise after Japan, with 74 percent of the population exposed to levels over what is considered tolerable. According to the recently released regulating bodies, noise is one of the top environmental threats throughout the European Region, both physical and mental wellness and well-being. (WHO, 2018).

According to World Health Organization estimates from 2017, an estimated 360 million individuals throughout the universe grieve from severe deafness as a outcome of noise pollution, with an estimated one billion young people aged 12 to 35 years old experiencing deafness as a result of noise exposure. According to Abdul-Majid *et al*. (2018), 8.5 million Nigerians suffer from earshot, while 466 million people are suffering from hearing loss globally. In a country of nearly 200 million people, 23.7 percent of Nigerians have hearing loss, according to Treat (2016) and Asonye *et al.* (2018). (total deafness, hearing loss, or any hearing-related impairment). An international organization like, WHO, EPA, NIOSH, OSHA, etc., had all agreed that constant noise exposure of 80 and 90 dB for 8-hours’ time-weighted average are harmful to human health **(WHO, 2018;** Fink, 2017; Munzel *et al.,* 2017).

Environmental Protection Agencies (EPA), in their pursuit to make environment safe to live had encouraged that researcher should study on the level of noise exposure within their locality, in other to determine the noise pollution level in their territories and justify their result with the permissible noise level limit (Zhou, J. (2012). The noise level of many cities in Nigeria are yet to be documented, of which Omu-Aran in Kwara State is one of them. Therefore, this study is ready to document, map, evaluate, and validate the noise level within the town.

## 1.2 Statement of the problem

Noise pollution has been reported as a key threat to comfort of people especially in urban and semi-urban areas (Bermudez *et al.* 2019; Vladimir and Madalina, 2019; Kalawapudi *et al.* 2020). Excessive noise has recently acquired a new characteristic: in addition to being a source of discomfort, it has been shown that persons who are subjected to high-intensity sound waves for lengthy periods of time lose their health (WHO, 2015). Numerous studies have linked lengthy and transient noise exposure to elevated blood pressure, heart illness, worry, and sleeplessness (Münzel *et al.* 2017). It has been discovered that semi-empirical approaches, such as regression analysis, do not provide reliable results in explaining noise pollution trends. Many authors have attempted to overcome these difficulties in noise prediction by adopting a neural approach (Nedic *et al*., 2014). It becomes difficult to quantify the impact of noise on those that are perceptible to it, primarily because noise can only be measured at exact occurring moment as it does not leave any residue once the source is dispersed (Piga *et al.* 2015). Also, there is poor or unavailable information about environmental noise pollution, and that its health impact data with the government, which made it a concern that there’s little or no research had been done on noise pollution level in Omu-Aran Township.

## 1.3 Aim of the study

The goal of this study is to use an artificial neural network to validate the noise level of Omu-Aran Township.

**1.4 Specific objectives**

The specific objectives are to:

1. document the noise level in Omu-Aran town using noise level meter
2. map the noise level in Omu-Aran Township
3. evaluate the health risk of noise pollution in Omu-Aran
4. validate the noise level using the Artificial Neutral Network Model
5. Evaluate the performance of Artificial Neural Network in terms of accuracy and root means square error (RMSE)

1.5 Justification of the study

Due to unavailable data on noise pollution in Nigeria, making a decision on solving the noise pollution threat to human health becomes more difficult and costly for the local authority. The noise level of many cities in Nigeria is still not well documented, which Omu-Aran in Kwara State is inclusive. As a result, a noise map and validation of Omu-Aran Township noise levels are required because the latest development of three private universities, over 20 public and private Secondary schools, not less than 35 public and private nusary and primary schools, one big central market and three community markets, and several industries springing up within the town in recent time, and had resuted to an increase in population and human activities. Therefore, through this study, public awareness concerning the level of noise that those activities can cause will be made, and also help the local authority in their decision making.

## 1.6 Scope of Study

The scope of this study is restricted to the measurement and mapping of noise levels, health risk assessment impact due to the effect of the noise level determined and using an artificial neural network to validate the noise level of Omu-Aran Township, Kwara State, Nigeria.

## 1.7 Significance of the study

The significance of the study is to bring the entire residents and communities of Omu-Aran Township to the awareness of noise levels within the town and its health implications, and also help the government to have records on noise pollution levels which will guide the decision-makers in policy formulation to mitigate the health and environmental effects of noise pollution.

## 1.8 Limitations of the study

The method of data collection is time-bound within all selected locations and the available input parameters that are measurable are limited for effective performance for the validation in the Artificial Neural Network model.

## 1.9 Expected outcome

This research work is expected to document, map, health risk assessment, and validate the noise level of Omu-Aran Township, and also carry out a health risk assessment study based on the noise level determined.

# CHAPTER TWO

## 2.0 LITERATURE REVIEW

## Noise

Sound is a pressure fluctuation that the human ear can sense, this sound comes to an individual at a pleasing level, this level of sound to some it’s not acceptable, and thereby its rendered or tagged as noise. Noise can only be measured by its loudness through its sound frequency using a noise meter, and this loudness is determined by the physical sound pressure variation detected by the human ear's sensitivity every second (Murphy & King, (2016). For example, of such is seeing someone listening to his favorite music even with ear plug, such person can be smiling, someone that entered into a ceremonial location where all the garget is put on high volume such individual can leave annoyingly because the sound level at such location creates a nuisance to him. Vehicular traffic operations or general mechanical operations, social gatherings such as hotels and motels operations, industrial operations, business centers operations, power generating operations, etc. are always a source of noise and can be unbearable to those around them. The World Health Organization (WHO) defines noise pollution as any sound level greater than 65 decibels (dB), with noise becoming harmful at 75 dB and unpleasant at 120 dB. Noise levels should probably be kept below 65 decibels during the day and at night to allow for comfortable sleep, with nighttime ambient noise levels of 30 decibels (WHO, 2018).

Noise is generally defined as the pressure variation that is not acceptable, unwanted, and unpleasing to the human ear, capable of annoying and hampering the mental physical health of man, animal, and plant, and also have the capacity of causing damage to health (Xiong et al., 2018). Pitch irregularities, duration, rhythm, and unexpectedness, as well as whether the noise has any meaning for the listener, all contribute to the level of discomfort induced by noise **(**Munteanu, G. (2010). Noise can be studied in a variety of settings, including indoor and outdoor activities, road traffic, railways, aircraft, factories, construction, and institutional and public activity.The World Health Organization had supported that researcher should a consider noise pollution research, and it is now up to each city in a country with a lot of noisy activities to estimate the degree of noise efects in their territory by generating noise maps (NIOSH,1998; 1999; OSHA; Stansfield & Matheson, 2003). A comfortable setting is one in which there is little or no aggravation or distraction, allowing physical and mental duties to be completed without interruption.

Environmental noise has unfortunately become a severe problem in many nations, and it is impossible to control just by physical measures(Onuu, 2000). Oyedepo *et al.* (2008) gave an evaluation analysis of noise pollution in Ilorin, where the result showed that out of the 42 locations selected, the noise level of 32 locations exceeded the allowable values of WHO. Results also showed that the noise level at Ile-Ife and Ibadan cities is 53dB and 89dB respectively which raised an alarm to compare to the permissible limit of WHO (Palamuleni, 2015). A study by Anomohanran (2013) also showed the noise pollution evaluation in Abuja in the day-time and the means noise level varies from 73.2 dB to 83.6 dB. The average noise level in Lagos was found to be 90.3 15 decibels, which is likewise beyond the allowed limit (Zaccheaus *et al.,* 2017). Also, Kano's noise level was found to be on an average of 80.4dB (Sani *et al.,* 2018).

According to Bond (1996), noise exposure causes physical ear discomfort at sound gravity levels of 80 to 100 decibels (dB). An incessant noise level of 85 dB has a number of serious side effects, including hearing loss. To describe how frequently the human ear reacts to noise, decibels (dB) are frequently used to measure noise (A). Over 40% of the populace is visible to transportation noise above 55dB(A), and the percentages in Europe and Japan are substantially advanced. The amount of noise that is present in the environment in the United States has been documented (OEDC,1993). Unlike many other environmental issues, noise pollution is still on the rise, along with an increase in complaints (WHO, 1999). Aside from that, noise has been proven to contribute to the level at which people make mistakes at work, and also mitigate the work rate or efficiency of every worker (Olawepo *et al.*, 2001). Consistence exposure to noise will affect the human quality of life e.g., sleeping, hearing, communication interference, disturbance, severe damage to the health of a human, animal and also impose a threat to the pollination of the flowering plants. Noise as a disturbance may result in various human diseases such as; hypertension, headache, ectopic beat, atheroscolysis, peptic ulcer, bradycardia, etc.

The maximum daily exposure time for a worker to various sound levels is outlined in OSHA's Table G-16. A dose of 100%, or the maximum permitted, is an 8-hrs contact to 90 dBA. A 100 percent dose is equivalent to 6 hours at 92 dBA. Lower doses would be associated with less-than-maximum times at a convinced level: 4 hours at 90 dBA would be a 50% dosage. Occupational Safety and Health Authority is shown in Table 2.1.

Table 2.1: OSHA's Table G-16 (Korea Industrial Health Association (2003).

|  |  |
| --- | --- |
| **Sound Level, slow response (dBA)** | **Duration per day (hours)** |
| 85 | 16 |
| 90 | 8 |
| 92 | 6 |
| 95 | 4 |
| 97 | 3 |
| 100 | 2 |
| 102 | 1.5 |
| 105 | 1 |
| 110 | 0.5 |
| 115 | 0.25 |

## Sources of Noise

Human activities are the major source of noise, starting from domestic and noise from leisure activities, transportation, commercial and construction, and building services noise. Transportation noise (road traffic, rail traffic, and air traffic) are all sources of noise humans encounter daily. Construction and building service noise is generated from various equipment, and tools used at the cause of construction, and this source of noise does not have regard or consider environmental consequences e.g., crane operation, concrete mixer operation, boring, welding, hammering, etc. In an urban setting people crave leisure and most of their focus is to enjoy their leisure time in hostels, motels, recreational centers, tourist centers etc., noise-producing gargets that create nuisance in the communities without the resident’s preparation for the abnormality. Sound may flow through a variety of elastic material, including air, water, wood, and metal. Below are various sources of noise with the average noise level generated as reported by Singh *et al.* (2004).

1. Highway noise is the noise that pollutes cities the most. For example, a bus' siren is 100 decibels louder than an automobile's horn, which is 90 dB.
2. Air traffic noise: Even though there are less planes hovering over cities than there are vehicles on the highways, their influence is more: One jet generates 130 d Construction sites:
3. Building, parking lot, and road and pavement resurfacing projects all produce a lot of noise. For instance, a pneumatic drill emits 110 dB.
4. Catering and nightlife: When it's nice outside, terraces, pubs, and restaurants can all emit noise levels above 100 dB. Noise from bars and clubs is categorized here..
5. Animals: The noise made by animals is commonly disregarded, yet a weeping or barking dog, for instance, can emit 60 to 80 dB.
6. Industrial activities: Production machinery could generate 100dB
7. Religious activities: the pollution in church,and mosque are 121.18, 119.38dB and 123.48dB for Pentecostal.

## 2.3 Types of Noise Sources

### 2.3.1 Point source

This type of noise source has to do with thedimensions of a noise source in which mostly the sound energy blowouts spherically.

The sound gravity is the same at all locations in relation to the noise cause, and it reductions by 6 dB for each copying of distance, as is the case with fans and chimney stacks.This remains constant until ground and air attenuation affects the level. Equation 2.1 was use to calculate the sound pressure level (Lp) at any distance (r, in m) sound power level (LW) from a specular reflection that is close to the ground:

2.1

### 2.3.2 Line Source:

A noise source that is long and narrow in one direction with regard to the listener's distance is referred to as a line source. It could come from a single point source, like a long pipe conveying turbulent fluid, or it might come from a number of different point sources, like a line of moving cars on a busy highway. Since the sound pressure level disperses cylindrical, it is constant along the line and decreases by 3 dB for every doubling of distance. Even until the level is affected by ground and air attenuation, this remains constant with regard to the listener's distance. Equation 2.2 can be used to calculate the sound pressure level (Lp) from a line source with a close-to-the-ground sound power level per meter (LW/m) at any distance (r, in m):

2.2

## 2.4 Related Review of Noise Pollution of some Cities in Nigeria

Research had been carried out in most of the highly populated cities in Nigeria, table 2.2 shows different conclusions made by the researcher.

## 2.5 Health Risk Assessment of Noise Pollution

Establishments and institutions, such as the World Health Organization (WHO), The National Institute for Occupational Safety and Health (NIOSH) and the Occupational Safety and Health Administration (OSHA) have been aware of the health concerns caused by noise since the 1970s. Noise pollution to humans according to these agencies are classified into two. These are: physiological effect which is auditory effects and they physically lead to the following: Hearing loss, an impairment, interference with speech communication, and sleep disturbance.

Table 2.2: Related Review of Noise Pollution of some Cities in Nigeria

|  |  |  |  |
| --- | --- | --- | --- |
| S/N | Name of Author | Conclusion | Year of Research |
| 1 | Onuu *et al.* | Environmental noise has unfortunately become a severe problem in many nations, and it is impossible to control just by physical measures | 2000 |
| 2 | Oyedepo *et al.* | an evaluation breakdown of noise pollution in Ilorin showed that the noise level of some of the selected areas exceeds the allowable values of WHO | 2008 |
| 3 | Palamuleni *et al.* | Ile-Ife noise levels of 53dB and 89dB which also exceeds the allowable limit of the WHO | 2015 |
| 4 | Anomohanran | Abuja in day-time and the means noise level varies from 73.2 dB to 83.6 Db | 2013 |
| 5 | Zaccheaus *et al.* | It was documented that the average noise level of Lagos was found to be 90.3dB | 2017 |
| 6 | Sani *et al.* | Kano noise level was found to be on an average of 80.4dB | 2018 |
| 7 | World Health Organization | 360 million people worldwide have substantial hearing damage as an outcome of noise contamination, while a valued 1.1 billion young people amid the ages of 12 and 35 experience deafness due to noise contact. | 2017 |
| 8 | Abdul-Majid *et.al* | 8.5 million of the Nigerian population have hearing problems, while 466 million people are suffering from hearing loss globally | 2018 |
| 9 | Asonye *et al* | 23.7 percent (36.7 million) of Nigerians, who number over 155 million, suffer from hearing loss (total deafness, hearing loss, or any hearing-related impairment). | 2018 |
| 10 | Münzel *et al.* | Noise damages earshot, but it also raises blood pressure, leads to heart disease, generates worry, and causes sleeplessness. | 2012 |

(headaches, weariness, and irritation), annoyance, and task performance (productivity, task performance, and distraction) (sense of annoyance, where acceptance varies greatly and noise instincts are more irritating than a sturdy noise), threshold shift or tinnitus, and non-auditory psychological effects (for example, frighten and defense responses leading to a probable growth in blood pressure, annoyance, affects student assimilation and learning, sleep trouble, physiological stress responses, and heart diseases, in addition to auditory shock, tinnitus, temporality, and cardiovascular (NIOSH, 1998).

The European Environment Agency evaluate that, each year, noise causes seventy-two thousand hospital admissions and 16,600 early deaths in Europe (Yuan et al., 2020). Animals suffer from it as well as humans when it is practiced. Noise pollution has a huge environmental impact and causes severe animal harm, according to the National Park Service (NPS) in the United States.

Noise pollution, according to specialists, can dislocate mating and rearing series, and may even speed extinction Valenti (2004). 30 million Americans are visible to dangerous noise, according to the National Institute for Occupational Safety and Health (NIOSH). In Nigeria's council of Owerri Metropolis, noise pollution is one of the leading causes of high rates of illness, particularly cardiovascular disorders and mortality. This continues to grow consequently of the perceived daily migration of people into the city and insufficient police enforcement to manage it (Okwudili *et al*., 2012).

### 2.5.1 Health Effects of Noise

After analyzing the available scientific data indicating causal relationship, Kim (2007) came to the conclusion that the following outcomes should be included:

1. heart disease
2. reasoning impairment
3. sleep fracas
4. tinnitus
5. aggravation

America Journal of public health in 2017 described Long or frequent exposure to sounds above 85 decibels can induce hearing loss, and 80-130 decibels can cause pain, which can lead to a variation of health complications. Environmental Protection Agency (EPA), and the National Institute for Occupational Safety and Health (NIOSH) Act of 1970 (Public Law 91-596, 1970, also agreed that a noise level of 80dB is harmful to human health (Fink, 2017). The Categories of noise level consequence is shown in Table 2.3.

## 2.6 Theory of Sound

**Sound:** Sound can be defined as the vibrations that transmit through mediums such as a gas, liquid, or solid, which propagate as wave to the brain of living things like a *r*eception and perception when heard through a human or animal's ear (Luce, 2013).

**Sound energy:** Sound energy is a type of energy that only living organisms can perceive. Is what happens when a force, such as sound or pressure, causes an item or substance to vibrate at a frequency that is audible to humans, between 16 Hz and 20 kHz. This range, however, is average and will vary slightly from person to person. Sound energy can be described numerically as;

*W= WPotential +Wkinetic* 2.3

Where W is the sound energy, Wpotential is the potential energy density and Wkinetic is the kinetic energy density.

## 2.7 Factors Affecting Sound Energy

1. Nature of Material/ Medium
2. Temperature.
3. The humidity of Air.

## 2.8 The Speed of Sound:

The distance covered per unit of time as a sound upsurge crosses an elastic material is referred to as the sound upsurge's speed. The temperature, for instance, has an impact on it. At 20 degrees Celsius, sound moves at a speed of around 343 meters per second (1,125 feet per second; 1,235 kilometers per hour; 767 mph; 667 kilometers), or one kilometer in 2.9 seconds, or one mile in 4.7 seconds (68 degrees Fahrenheit). The speed of sound is highly influenced by temperature and the intermediate over which it travels. Sound travels at 331 m/s (1,086 ft/s; 1,192 km/h; 740 mph; 643 Kn) at 0 °C (32 °F) (Moustakidis et al., 2017). As a result of particle-to-particle contact, a sound wave is a pressure imbalance that travels across a intermediate.A force to the next nearest particle when one particle is disturbed.As a result, the particle is roused from its state of relaxation and the energy is transmitted across the medium.

Table 2.3: Categories of noise level consequence ((Ma *et al*., 2017).)

|  |  |  |
| --- | --- | --- |
| categories | noise level (dB) | Consequences |
| level 1 | 30-60 | Disorders such as confusion, discomfort, irritability, sleep, and others |
| level 2 | 65-90 | Physiological responses |
| level 3 | 90-120 | Headaches and improved physiological responses |
| level 4 | 120 | Internal ear injury is permanent, and balance is compromised |
| level 5 | 140 | Significant brain damage |

Like all waves, the speed of a sound wave is the rate at which the disturbance is transferred from one particle to another (Murray, 2019). Mathematically, the speed of sound can be expressed as:

**Speed = 2.4**

A sound wave can cover more space in the same amount of time if it travels quicker. The speed of a sound wave that travels 700m in 2s is 350m/s. A slower wave would cover less ground in the same amount of time - possibly 660 meters - and hence have a speed of 330 meters per second. In the same amount of time, faster waves cover greater distance (Moustakidis *et al*., 2017).

### 2.8.1 Speed of Sound in Different Materials

Sound moves sluggishly in gases, fast in liquids, and very quickly in solids, depending on the condition of the substance (Beisteiner et.al., 2020). While sound moves at a speed of 343 meters per second in the air, it moves at 1,481 meters per second through water (almost 4.3 times faster) and 5,120 meters per second through iron (almost 15 times faster than air). In a hard substance like diamond, sound travels at roughly 12,000 meters per second, nearly 35 times faster than in air and the wildest it can journey under normal situations.

### 2.8.2 Factors affecting the speed of sound

1. The Density of Medium: Sound needs a medium to travel. The density of those medium varies, from substance to substance which makes it a factor that affects the speed of sound.
2. The Temperature of The Medium: Advanced the temperature, the complex the speed of sound in the medium.

## 2.9 Sound Pressure (Pa)

It is the sound force (N) operating on a surface area (m2) that is vertical to the route of the sound source. Pa or N/m2 is the sound pressure unit in the SI system. Sound pressure-responsive microphones, or noise meters, are frequently used to measure sound. The square of the pressure is how powerful a sound upsurge becomes. (The square of the voltage is proportional to electric power.) When converting pressures to decibels, the log of the square of x is merely 2 log x, introducing a influence of two (vec & Granqvist, 2018). Table 2.4 displays the different noise sources and their hearing thresholds.

### 2.9.1 Measuring Sound Pressure:

Most Sound Level Meters reads the effective sound pressure which can be stated as

pe = pa / 21/2                           2.5

where, pe = restrained (effective) pressure (Pa)

pa = extreme pressure breadth in the sound upsurge (Pa)

## 2.10 Human Ear

**The human ear is a balancing and hearing organ that detects and interprets sound by maintaining balance by turning sound waves into electrochemical impulses. Hearing and postural equilibrium, as well as synchronization of head and eye movements, are two distinct functions of the human ear, which it shares with other mammals**. Anatomically, the ear is split into three parts: the middle, outer, and inner ear. The small external auditory canal and the auricle, also known as the pinna, which protrudes from the side of the head, comprise the outer ear. The tympanic membrane, also known as the eardrum, closes the inner end of the external auditory canal (Heffner et al., 2007). coming from and to transmit that sound to the middle ear.Before sending sound to the cochlea through the ossicles, the middle ear corrects the impedance mismatch between air and liquid.. The cochlea provides balance and converts mechanical vibrations into nerve impulses (Talaska et al., 2007). The location theory and the temporal theory are two different types of hearing theories that might work in different frequency ranges (Oxenham, 2013).

### 2.10.1 How Noise Affects Human Ear

The cochlea is the inner ear's complex, spirally coiled, tapering cavity where sound vibrations are transformed into nerve impulses. The cochlea's cells and membrane can be harmed by prolonged exposure to loud noise because of the vibration caused by the sound waves. Long-term exposure to loud noise can stress out the hair cells in the ear, which can lead to these cells packing up or dying. As long as the victim does not try to stop being exposed to it, the hearing loss gets worse(Talaska *et a*l., 2007). Harmful effects will continue even when the exposure had been stopped. Tinnitus is most commonly produced by impairment to and loss of the small sensory hair cells in the inner ear's cochlea.

Table 2.4: Source of Noise and their Different Threshold of Hearing, Trevino & Lobarinas (2021).

|  |  |
| --- | --- |
| Source | Sound Pressure Level(dB) |
|  |  |
| Threshold Hearing | |
| Softest distinct sound for individual with an excellent hearing under laboratory condition2 |  |
| Softest distinct sound for individuals under regular conditions | |
| Victual calm, barely perceptible  Audio-metric test room | 10 |
| Whisper leaves  Mosquito | 20 |
| Noticeable Quit – Voice, soft whisper | |
| Noiseless whisper (4ft. 1m) | 30 |
| Home  Noiseless room  Birds call | 40 |
| Moderate | |
| Noiseless street  Noiseless office  Held speech | 50 |
| Vulgar – Voice discussion 1ft, 1m | |
| Normal conversation at 4ft, 1m | 60 |
| Laughter | 65 |
| Loud – Voice conversation 1ft, 0.3m | |
| Private car  Traveler car 80km/h, 50mph (50 ft, 15m)  Void cleaner (10ft, 3m)  Freight Train (100ft, 30m)  Related discussion restaurant | 70 |
| Vulgar singing  Car ambitious at 105km/h, 65 mph  Washing machine | 75 |
| Loud – Unbearable for phone use | |
| Food blender (4ft, 1m)  Extreme sound for up to 8 hours (OSHA earshot management program standards)  inflated tools (50ft, 15m)  Buses, trucks, and motorcycles (50ft, 15m)  A car wash (20ft, 6m)  Road with busy traffic | 80 |
| A food processor (4ft, 1m)  Up to 8 hours of continuous sound (OSHA criteria -engineering or administrative noise controls)  hammering (50ft, 15m)  Excavator (50ft, 15m)  Factory Noise Broadsheet Press Subway (inside) | 88 |
|  | 94 |
| Very Vulgar | |
| Dissel truck (30ft, 10m)  Motor sirens at distance of 7m | 100 |
| Lawn mower (4ft, 1m) | 107 |
| Pneumatic riveter (4ft, 1m) | 115 |

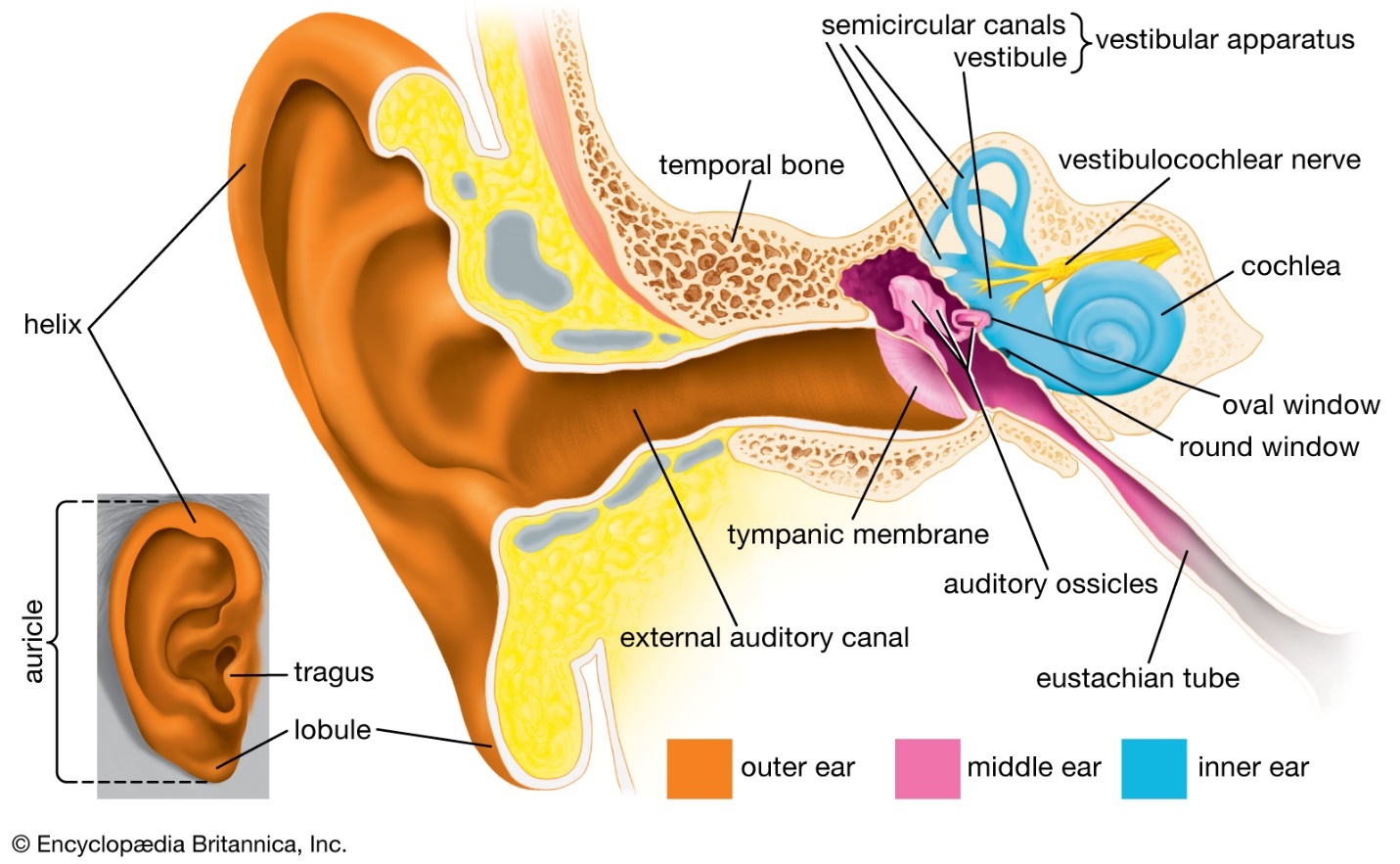
**Table 2.4: Source of Noise and their Different Threshold of Hearing Cont’d**

|  |  |
| --- | --- |
| Threshold of worry | |
| Huge aircraft (500ft, 150m overhead)  Power saw | 110 |
| Chainsaw (4ft, 1m)  Very loud work – boilermakers’ workshop, etc. | 117 |
| Ear-piercing, Human ache limit | |
| Augmented Hard Rock (6ft, 2m)  Alert (100ft, 30m)  Inflatable chipper  Drums | 120 |
| Jet plane (90ft, 30m)  Weapons Fire (10ft, 3m) | 130 |
| The high limit for insecure ear for instincts  Threshold pain | 140 |
| Short contact can cause earshot loss | |
| Armed Jet Take–off (100ft, 30m) | 150 |
| Huge military weapons | 180 |

This is more common as people get older, but it can also arise as a consequence of persistence contact to overly loud noise. Tinnitus and hearing loss may occur together (Liberman et al., 2017). Figure 2.1 depicts the anatomy of a human ear.

## 2.11 [Frequency](https://www.physicsclassroom.com/class/sound/Lesson-2/Pitch-and-Frequency) of sound

This is the amount of vibrations or how often a particular particle may make per unit of time, whereas The disturbance's speed is the distance it travels per unit of time. The human ear is

  
Fig 2.1: Description of Human Ear (Encyclopedia)

Most sensitive to and quickly recognizes frequencies between 1,000 and 4,000 hertz, but the full hearing range of sound frequency spans from around 20 to 20,000 hertz for normal young ears. Ultrasonic sound waves are higher frequency sound waves that can be detected by other mammals. Table 2.5 displays the hearing frequency ranges of many animals.

### 2.11.1 Factors affecting the sound frequency

1. Effects of Temperature
2. Effect of Density: At constant pressure,
3. Effect of humidity
4. Effect of Wind
5. Effect of frequency wave length & amplitude

Owls and other animals with their relative orientation can adjust their outer ears or turn their complete heads to better discern the true source of sounds. Deer, for example, have muscles that allow them to point their pinna in various directions, which aids predator detection (humans have atrophied versions of these same muscles but they no longer produce much motion of the ear) (King, 2009).

## 2.12 Noise Mapping

A noise map is a graphical depiction of the spreading of sound levels and the propagation of the sound waves in a given place of interest for a specific period. The detail of the location will be provided by noise mapping in a very simple concept, a visual representation in form of a contour map, usually colored for easy indication, to get the noise intensity, and also frequency variation of a specific point of interest. Technology engaged by humans to carry out daily activities either domestic, industrial, commercial, institutional or social operations all are the source of noise and this resulted in environmental dissatisfaction, so to monitor and asses the influence or impact of noise in a given locality.

A lot of policies had been made available by the European countries and in other to support this policy noise effect research is carried out. The result of different researchers can only be combined and compared, so it is therefore important to develop an advanced method for noise mapping (De Kluijver *et al.*, 2003). Literature had showed that many researchers choose different measurement

Table 2.5: Hearing Frequency differences in both Humans and Some Animals

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| S/N | Animals | Frequency | Conclusion | Year Of Research | |
| 1 | Human | 20-20000 | The human ear is most delicate to and perceives frequencies between 1,000-4,000 htz, whereas the complete audible range of sound frequency for typical juvenile ears is between 20 and 20,000 hertz | Gaetán, *et al*., (2021) |
| 2 | Bats | 2000-110000 | The most of bat sound waves takes place above or below human hearing thresholds.Depending on their age, humans can hear frequencies between 20 Hz and 15-20 kHz.  Bat cries can have a frequency between 9 and 200 kHz.. | Armitage & Ober (2010). |
| 3 | Elephant | 16-12000 | Elephants have large, flat ears that are more sensitive to lower frequencies of communication. | (Heffner *et al*., 2007), |
| 4 | Whale | 1000-123000 |  | (Heffner *et al*., 2007), |
| 5 | Dog | 67-45000 | Your dog might bark in response to another dog barking down the block. Because a dog's hearing ranges from 40 to 60,000 hertz, this is the case (remember: humans hear between 20 and 20,000). Dogs, on the other hand, have extraordinary hearing, being able to detect sounds as low as -15 dB. | (Heffner *et al.*, 2007), |
| 6 | Cat | 45-64000 |  | (Heffner *et al.,* 2007), |
| 7 | Rat | 200-76000 | Because birds of prey are predators, rats develop larger hearing, making them more sensitive to sounds from above | (Heffner *et al*., 2007), |
| 8 | Chicken | 125-2000 |  | (Heffner *et al.,* 2007), |
| 9 | Horse | 55-33500 |  | Timney & Macuda (2001) |
| 10 | Lion | 450-50000 | Lions have excellent hearing. Lions' ears can turn from side to side to pick up noises from practically any direction. They can hear prey from over a mile distant | (Heffner *et al.,* 2007), |

methods in determining, evaluating, and mapping noise levels over different territories, When these investigations were examined, identical measuring methods and measurement times were discovered (Karakus and Yldz, 2020; Oguntunde et al. 2019, Farooqi et al. 2017, Rafael et al. 2015; Kephalopoulos et al. 2014) have used periods. The Geographical Information System was used, and Arch-GIS was chosen for this study because of its high resolution and accuracy (Google Earth, 2018).

### 2.12.1 Noise mapping tools for developed and developing countries

According to the literature, most researchers in Africa, Asia, and Europe used various terrestrial information systems (GIS) as a tool for producing 2D and 3D noise maps. Also, in some countries, the use of additional tools such as soundplan for producing 2D and 3D noise mapping has been investigated. Zannin *et al*. (2015) in Brazil, for example, provided extensive details on the evolution. Wu *et al*., (2018) in China used Swallow sound for the progress of a 2D noise map in their research. Also, the generation of 2D and 3D noise mapping for the nominated site in Latin America using Predictor 8.11. In Spain and Brazil, CAD 3D software was utilized for 2D noise mapping exclusively in Madrid and Brasilia; Kartikey Tiwari *et al*. (2017) in India; Vasilyev (2017) in Russia; Wu (2015) in China, Olayinka (2012) in Nigeria; Paulo and David (2011) in Brazil. SoundPlan software uses complex flittering algorithms that accept the user-defined tolerance. It also includes a number of tools for data training, constancy checks, and report certification (Hadzi-Nikolova *et al.,* 2012). Only a few scholars have generated 3D noise plots for a specified location of some nations, according to Alam *et al*., (2020). Arch-GIS will be examined in this study due to its excellent accuracy and resolution (Google Earth, 2018).

## 2.13 Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) are a form of artificial intelligence that have been around since the 1940s, when McCulloch and Pitts developed the first neural model. This development has sparked a lot of interest among researchers and other areas of application for artificial neural networks, resulting in more powerful networks, better training algorithms, and better hardware. The biological model of the human brain inspired ANNs as a learning and automated processing paradigm. They can simulate brain functions like learning. Artificial neurons (ANs), also known as elemental processors, provide the basis of ANNs. These neurons are connected in the same way that they are in the biological brain, with a high density and parallelism connectivity schema and weighted synapses whose alteration indicates network learning. Each AN is a node that processes data from several inputs and produces output in response to the stimuli it receives..

In most papers, fuzzy approaches are used to forecast noise irritation and degree of noise. Hidden Markov Models, on the other hand, have been the most widely employed for categorization. Genetic algorithms have a few references, and artificial neural networks are hired in a variation of domains, plus traffic flow classification and prediction. The network's results were compared to those of existing mathematically-based urban noise prediction models. Tests verified that the outcomes provided by the network are improved in all data records, indicating that the ANN's global learning is excellent (Genaro, 2010).

According to Kumar *et al.* (2012), due to the inclusion of various parameters on which noise level varies, modeling and prediction of traffic noise using traditional methodologies is a very difficult and nonlinear process. Researchers and acoustical engineers have used artificial neural networks in the field of traffic noise prediction to solve these issues. Following a careful examination of several neural network-based models established for road traffic noise validation described in the literature, it was shown that ANN-based models could predict traffic noise more precisely and effectively than deterministic and statistical models.

The multilayer perceptron (MLP) is a type of feed-forward propagation ANN that consists of layers of neurons with no feedback, i.e., a one-way operation. The network was trained using back propagation, a supervised learning technique. MLP is made up of three layers, as seen in Figure 2.2. Each node, with the exclusion of the input nodes, is a neuron with a non-linear activation function.

### 2.13.1 How Multilayer perceptron (MLP) Works in ANN

MLP works when all the layers are fully connected, the input parameters push the information to the hidden layer for processing with the help of the activation functions. Once the calculated output at the hidden layer has been proceeded through the activation function, the next layer in the MLP.

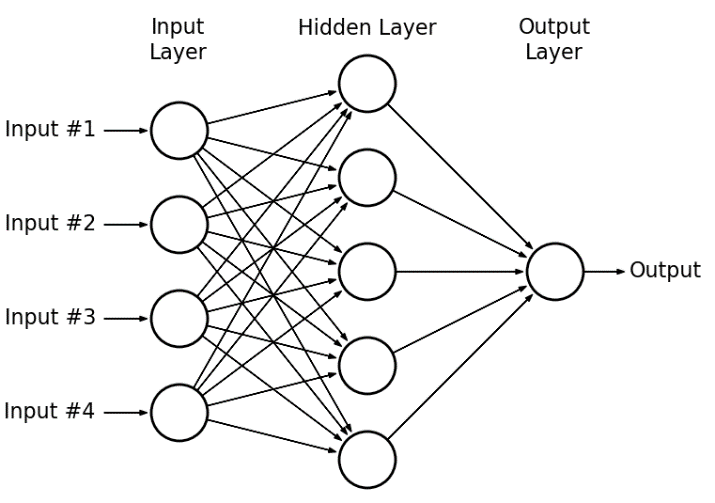


Fig. 2.2: Schematic Example of Multilayer Neural Network Perceptron (Genaro, 2010).

accepts it as input by taking the dot product with the corresponding weight. The activation function aids in the transformation of the weighted sum of all input into an output.

# CHAPTER THREE

## 3.0 Materials and Methods

## 3.1 Description of Study Area

Omu-Aran is a city in Irepodun local government in the southern fragment of Kwara State, Nigeria. Omu-Aran is located at latitude 8.13 º North, longitude 5.1º East, and at an elevation of 495 m above sea level. Omu-Aran was 148,610 in population conferring to the 2006 survey across a land area of 73.7 km2 (Elemile *et al.* 2019). The average weather condition are known to be temperature of 26º C, Wind at 13km/h, and Humidity of 74%. Omu-Aran has one general Hospital and more than three private hospitals. Also, aside from that Omu-Aran has two commercial markets, three community markets and a lot of supermarkets. It is a city that also, over 20 public and private Secondary schools, not less than 35 public and private nusary and primary schools, and several industries. Omu-Aran is a city with three private Universities which are Landmark University, Thomas Adewumi University, and Moses Orimolade University.

## 3.2 Measurement of Noise Level

Pressure difference that the human ear can notice is known as sound, and this sound level can be measured by a sound level meter. As a result, the sound level of each place was measured in this study using a sound level meter model SL4010. The sound meter contains a microphone with measurement quality, a mic preamp, frequency weighting networks, an RMS detection circuit, averaging circuits, a meter display, and AC and DC outputs for connecting to further measuring equipment or for recording. Low sound levels of 30 to 100 dB and high noise level of 60 to 130 dB are the settings. The microphone was focused to the noise source at a distance of not less than 1.6m above ground level, and the sound level meter was comfortably handled in one hand. Within Omu-Aran Township, the normal distance amid each of the designated locations is 200 50m, with an normal distance of 1km between each zone. Omu-Aran city was divided into three zones, each zone consist of seven locations, for a total of twenty locations. Data was gathered daily between the hours of 7-9 a.m; 12-2 p.m; and 4-6 p.m. for six working days over the course of three weeks, as indicated in Table 3.1. The data was collected starting from December 20th  -January 7th during school vacation, and for the first one week of school resumption.

Table 3.1: Zoning of study location

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Zones** | **Street** | **Co-ordinate** | **Elevation(m)** | **Time** |
| A | Oke-Agbede | 8º07ʾ06.7ʾʾN 5º05ʾ37.9ʾʾE | 559 | 7- 9 am; 12-2 pm; 4-6 pm |
| Landmark junction | 8º07ʾ27.6ʾʾN  5º05ʾ42.7ʾʾE | 547 | 7- 9 am; 12-2 pm; 4-6 pm |
| High Court junction | 8º07ʾ44.9ʾʾN  5º05ʾ50.1ʾʾE | 546 | 7- 9 am; 12-2 pm; 4-6 pm |
| Latinwo Market | 8º08ʾ05.9ʾʾN  5º05ʾ49.1ʾʾE | 550 | 7- 9 am; 12-2 pm; 4-6 pm |
| Ile-Nla | 8º08ʾ12.9ʾʾN  5º05ʾ57.8ʾʾE | 554 | 7- 9 am; 12-2 pm; 4-6 pm |
| Falaye | 8º07ʾ55.8ʾʾN  5º05ʾ41.8ʾʾE | 549 | 7- 9 am; 12-2 pm; 4-6 pm |
|  | Landmark Chapel | 8º07ʾ22.1ʾʾN  5º04ʾ59.2ʾʾE | 548 | 7- 9 am; 12-2 pm; 4-6 pm |
| B | Central Market | 8º08ʾ20.1ʾʾN  5º06ʾ11.0ʾʾE | 556 | 7- 9 am; 12-2 pm; 4-6 pm |
| Central Roundabout | 8º08ʾ09.8ʾʾN  5º06ʾ02.9ʾʾE | 539 | 7- 9 am; 12-2 pm; 4-6 pm |
| Iganngu/Okeki | 8º08ʾ27.9ʾʾN  5º06ʾ20.1ʾʾE | 546 | 7- 9 am; 12-2 pm; 4-6 pm |
| Ile-Olupo/Ile-Adee | 8º08ʾ20.1ʾʾN  5º06ʾ11.0ʾʾE | 539 | 7- 9 am; 12-2 pm; 4-6 pm |
| Odo-Areyin | 8º08ʾ02.1ʾʾN  5º06ʾ11.8ʾʾE | 534 | 7- 9 am; 12-2 pm; 4-6 pm |
| Egbe Garage | 8º07ʾ39.1ʾʾN  5º06ʾ27.1ʾʾE | 524 | 7- 9 am; 12-2 pm; 4-6 pm |
| Otolorin/Federal Hospital Junction | 8º07ʾ35.9ʾʾN  5º06ʾ48.8ʾʾE | 521 | 7- 9 am; 12-2 pm; 4-6 pm |
| C | GRA | 8º08ʾ10.2ʾʾN  5º06ʾ40.5ʾʾE | 531 | 7- 9 am; 12-2 pm; 4-6 pm |
|  | Agamo | 8º08ʾ24.0ʾʾN  5º06ʾ26.8ʾʾE | 521 | 7- 9 am; 12-2 pm; 4-6 pm |
|  | Taissa Junction | 8º08ʾ45.6ʾʾN  5º06ʾ36.3ʾʾE | 529 | 7- 9 am; 12-2 pm; 4-6 pm |
| Bovas | 8º08ʾ52.6ʾʾN  5º06ʾ25.0ʾʾE | 525 | 7- 9 am; 12-2 pm; 4-6 pm |
| Orolodo/Olomu Palace | 8º08ʾ52.6ʾʾN  5º06ʾ25.0ʾʾE | 548 | 7- 9 am; 12-2 pm; 4-6 pm |
| Secretariate/Eco Bank | 8º08ʾ40.5ʾʾN  5º05ʾ54.2ʾʾE | 549 | 7- 9 am; 12-2 pm; 4-6 pm |
| Taiwo | 8º08ʾ37.0ʾʾN  5º05ʾ50.5ʾʾE | 557 | 7- 9 am; 12-2 pm; 4-6 pm |

## 3.3 Mapping of Noise Level

The noise level gathered from all the selected locations and zones was mapped using ArcGIS 1 0.3 as one of the most efficient geographical information systems (GIS) as used by Kurakula *et al.* (2008) and Hadzi-Nikolova *et al*. (2012).

## 3.4 Health Risk Assessment of Noise Levels

The recommended exposure limit (REL) and permissible exposure limit (PEL) were developed by the National Institute for Occupational Safety and Health (NIOSH) and the Occupational Safety and Health Administration (OSHA), that any noise exposure between 80 and 90 decibels for eight hours is harmful to human health (WHO, 201; Fink, 2017; Munzel *et al*. 2020). In this research, the recommended noise limit of NIOSH, OSHA which is also acceptable by the Environmental Protection Agency (EPA) and World Health Organization (WHO) through their developed equation of LEX, 8-h for both REL and PEL over an 8-working hours’ time-weighted average per day was used. And the REL and PEL for each location of research were calculated by the equation (1) and (5) and the noise dose was calculated using equations (6) and (7). Equation (3.4) given by Occupational safety health authority (OSHA) was used to calculate the permissible noise exposure based on several sources of noise.

LEX, 8-h = 10 3.1

t=  = = 3.2

LAeq avg = 103.3

LTotal = 10log [ + 3.4

T=  3.5

D=  3.6

TWA = 90 + 16.61 log D 3.7

Where LEX is the average noise exposure value in decibels, at which there is a risk of hearing loss, t is the entire sample time of exposure in hr, and LEX is the estimated base of 8-h of time-weighted exposure. The logarithm average of noise levels per location during the day is LAeq avg, wi is the equivalent sound level average in decibels, and n is the number of measurements per location during the day. T is the maximum exposure period (hours), L is the sound pressure level (dB), and C is the actual exposure time in hours, which is 8 hours each day..

## 3.5 Validation of Noise Level Using the Artificial Neutral Network Model

In this research, Google Collaboratory was used as a platform for learning and for deploying machine learning algorithms using Python 3.6. 9. It is a modern development for all researchers using deep machine learning like ANN for analysis. It's an online platform that allows researchers to collaborate, allowing Google team members to share and edit and save notebooks simultaneously from anywhere. This is in agreement with Gunawan, (2020): Collaboratory is a web-based Python editor that permits anyone to write and run arbitrary Python code. It's remarkably useful for machine learning, data analysis, and education.

ANN comprises embedded formulas which had been interpreted into different python algorithm codes. Data uploading from googles drive to google Collaboratory in a Csv file that will enable the model to process the data into needed results. Installation of libraries like Pandas, Keras, TensorFlow, Sklearn, and Matplotlib which are necessary for: model exploration and loading of data, implementation of neural network (ANN), building and analyzing of the model, training of the model. Keras was used to build the model to predict if noise can be increased by the impact of the input features (Roman *et al.,* 2021).

### 3.5.1 Building of ANN Model

Selecting a problem field, establishing the network's topology, with the number of units in each input, output, and hidden layer, training and testing parameters, and tolerance levels are all part of creating an ANN model. Gunawan (2020) and Shah et al. (2013) agreed that a learning paradigm should be used for training the network and that the trained network should be evaluated for unknown samples for at least (70%) of the total data uploaded and (30%) of the total data uploaded as the testing sample.

A total of 1008 data was loaded, 70% of the data was adopted by the network to train and 30% of the data were considered for testing. This is in arrangement with the report of Mansourkhaki *et* *al.* (2018) and Dehra (2016) that ANN gives an excellent performance in noise prediction when the training and the testing dataset is well defined. Importation of algorithms and selection of epoch value based on the number of hidden layers chosen (in this research two hidden layers was used and 10 epochs were selected).

#### 3.5.1.1 Uploading of Data

Uploading of data from google drive to google Collaboratory, importation of libraries from Keras, TensorFlow, and matplotlib which are necessary for: exploring and data processing, building, and training of the model, loss and accuracy visualization of the trained model, and plotting of graph to show the model performance. Keras was used to build the model to predict if noise can be increased by the impact of the input features stated in Table 3.2. The process engaged was listed below;

1. Reading data from a CSV file and converting it to a format that the algorithm can understand (Array).
2. Splitting of the dataset into the input features (X, Y)
3. Data normalization i.e., Scale the data so that the input features are of comparable magnitudes.
4. Division of dataset into two parts: testing and validation/traning

The uploaded data comprises of input layers of 21 features which include: population, source of noise, noise level determined, air temperature and relative humidity, the width of the street, type of structure, the height of measuring instrument above the ground level, measuring instrument distance from noise source, wind speed, the height of the instrument, type of pavement, type of street layout, annual percentage change in population. The output layer was trained to give the efficiency of the model in the percentage of accuracy and precision based on the ability of the input data. All this was justified by plotting the confusion matrix of the trained data.

This research considered the use of Rectified linear Activation (ReLU) and Sigmoid function('sigmoid’) as the activation function, because of their simplicity of implementation and their effectiveness in overpowering the boundaries of other previous prevalent activation functions, such as Sigmoid and Tanh.

The ReLU function is calculated as:

*max (0.0, x) ……………………………….* 3.8

This means that, if the input value X is negative, then a value of 0.0 is returned, else, the value is returned (Brownlee *et* *al.* 2019).

S(x)= 3.9

where s is the input and x is the output. The sigmoid activation function guarantees that the output of this unit will always be between 0 and 1. Figure 3.1 shows the neural network architecture that was used or our problem

1. Hidden layer 1: ReLU activation in 32 neurons
2. Hidden layer 2: ReLU activation in 32 neurons
3. Output Layer: Sigmoid activation, 1 neuron

### 3.5.2 Training of Model

The model's architecture included a 15-neuron input layer, 32-neuron hidden layer 1 (ReLU activation), 32-neuron hidden layer 2 (ReLU activation), and a single-neuron output layer (Sigmoid activation).The layers listed above saved our model in the variable'model,' and were described progressively (layer by layer) in the square brackets as seen in equation 3.10.

Model = Sequential ([…]) 3.10

The first layer was a dense layer with 32 neurons that was used to fully connect all of the layers, ReLU activation, and the input shape was 15 because there were 15 input characteristics. The second layer, ReLU activation, was also dense with 32 neurons, while the third layer, sigmoid activation, was dense with only one neuron. The 'fit' function was used to fit the parameters to the data. The data we're working with is referred to as X train and Y train. Then we determined the batch size and duration of training (epochs). Finally, we supplied the validation data in order to govern the model's performance at each stage. Eqn. 3.11 displays the function's output as a history, which was later utilized to visualize the model's performance.

hist = model.fit(X\_train, Y\_train,

*batch\_size=32, epochs=10,*

*validation\_data=(X\_val, Y\_val))* 3.11

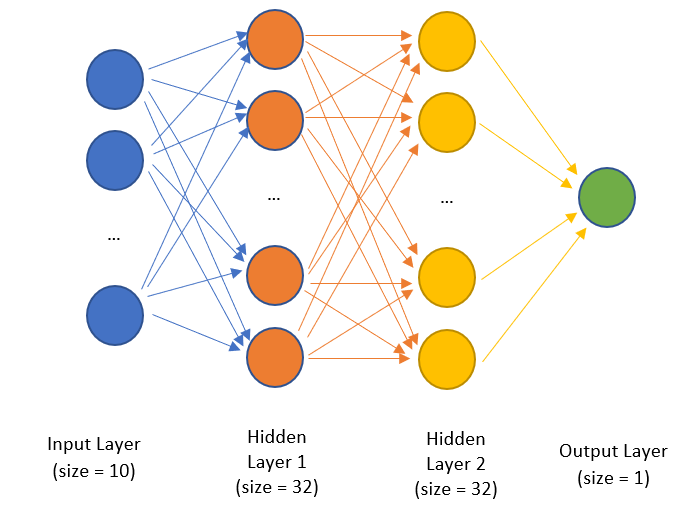


Figure 3.1: Neural network architecture that was used or our problem

Based on the natural and artificial characteristics at each selected location, Table 3.2 shows the parameters that are selected as a function on the input layer in MLP. Table 3.3 shows input variables/parameters for prediction.

## 3.6 Data analysis

The data was analyzed using the Statistical Package for Social Science (SPSS), with a one-way ANOVA at a significance level of 0.05.

Table 3.2: Input Parameters for Validation

|  |  |
| --- | --- |
| S/N | Input Parameters |
| 1 | Position of the measurement station, |
| 2 | Height of the measuring instrument |
| 3 | Time of day |
| 4 | The average elapsed time of reading |
| 5 | The population of the street |
| 6 | Type of the street |
| 7 | Width of the street |
| 8 | The average elevation of buildings |
| 9 | Width of the road |
| 10 | Average distance between selected location |
| 11 | wind speed and direction, |
| 12 | air temperature and relative humidity, |
| 13 | Number of lanes |
| 14 | Type of the pavement |
| 15 | Distance from the noise source to the receiver |
| 16 | The average height of buildings |
| 17 | Noise source type |
| 18 | Type of structure/ building |
| 19 | Annual percentage increase in population |

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 3.3: Input Parameter Data for Validation | | | | | | | | | | | | | | | | | | | | | |
| **Location** | **Population** | **Av. No Noise Source** | **No.of reading per location** | **Av. Time of reading(s)** | **Type of road** | **Width of the road(M)** | **Number of lanes** | **Av. Height of Barriers /structure** | **Anul. changein population per Annum (%)** | **Av.noise source dist.(M)** | **Height of the measuring instrument (M)** | **The average number of samples per day** | **The average elapsed time of reading (second(s)** | **Av distance between selected location (M)** | **Av wind speed direction(mph/ WEST)** | **Av air temperature (°C)** | **Av relative humidity, (%)** | **Av Distance of Instrument from the noise source(M)** | **Type of structure/ building** |  |  |
| OKE- AGBEDE | 3000 | 1 | 1 | 30 | 1 | 7.4 | 2 | 7 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| LANDMARK JUNCTION | 2500 | 2 | 1 | 30 | 1 | 7.4 | 2 | 7 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| HIGH COURT JUNCTION | 6200 | 3 | 1 | 30 | 1 | 7.4 | 2 | 5.5 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| LATINWO MARKET | 8500 | 3 | 1 | 30 | 2 | 4.6 | 2 | 14.5 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| FALAYE | 5100 | 2 | 1 | 30 | 3 | 3.25 | 1 | 7 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| ILE-NLA | 7800 | 3 | 1 | 30 | 2 | 4.6 | 2 | 9 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| CENTRAL ROUNDABOUT | 12200 | 3 | 1 | 30 | 1 | 7.4 | 2 | 15 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| CENTRAL MARKET | 12000 | 3 | 1 | 30 | 1 | 7.4 | 2 | 6 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| IGAN-NGU/ OKEKI | 9000 | 3 | 1 | 30 | 2 | 4.6 | 2 | 14.5 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| ILE- ADE | 6000 | 3 | 1 | 30 | 2 | 4.6 | 2 | 14.5 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| AGAMO | 5000 | 3 | 1 | 30 | 3 | 3.25 | 1 | 7 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| ODO- AREYIN | 7000 | 2 | 1 | 30 | 3 | 3.25 | 1 | 7 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| EGBE – GARAGE | 4500 | 2 | 1 | 30 | 3 | 3.25 | 1 | 7 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| OTOLORIN | 3500 | 2 | 1 | 30 | 1 | 7.4 | 2 | 14.5 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| GRA | 2400 | 2 | 1 | 30 | 3 | 3.25 | 1 | 15 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| TAISSA JUNCTION | 4200 | 3 | 1 | 30 | 1 | 7.4 | 2 | 7 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| BOVAS | 2000 | 2 | 1 | 30 | 1 | 7.4 | 2 | 7 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| OLOMU-PALACE | 5000 | 3 | 1 | 30 | 3 | 3.25 | 1 | 7 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| SECRETARIATE | 6000 | 3 | 1 | 30 | 1 | 7.4 | 2 | 15 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| TAIWO | 5000 | 3 | 1 | 30 | 2 | 4.6 | 2 | 7 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |
| LANDMARK CHAPEL | 5000 | 2 | 1 | 30 | 2 | 4.6 | 2 | 20 | 2.3 | 3 | 1.6 | 3 | 30 | 250 | 7.7 | 31 | 58 | 2.5 | 1 |  |  |

# CHAPTER FOUR

# ANALYSIS AND DISCUSSION

The results for the Omu-Aran Township noise level are presented in this chapter. The 21 places chosen were researched for three weeks, with data collected thrice daily (morning, afternoon, and evening). Apart from the input variable data utilized in creating the ANN model, 1134 data on noise levels were gathered over the course of 8 working hours. Descriptive analysis tool was used to analyze all the data, and a one-way ANOVA was performed with a P-value of 0.05. Using descriptive analysis, the mean total and standard deviation for each location were calculated. The mean total and standard deviation were then used to calculate the equivalent average noise level (Leq.) using the logarithm total formula as shown in equation (3.3), all in accordance with OSHA, EPA, and NIOSH recommendations (Fink, 2017; Munzel et al (2017, 2020).

## 4.1 Determination of Noise Level in Omu-Aran Town

### 4.1.1 Mean Noise Levels in the Morning

Figure 4.1 expressed the mean noise level in the morning. A total of 378 data were collected in the morning across all selected locations. The average mean value of noise level in all locations in the morning was gotten to be 67.82± 2.1dB. Landmark University Chapel is the noisiest with 82.5dB, Central roundabout, and Central market is visible to 79.11 and 78.24dB respectively, and all other locations are exposed to noise pollution below the mean average with 67.82 ± 6.24dB in the morning. Landmark University Chapel is unprotected to the highest noise level above the acceptable while Central roundabout, and Central market are unprotected to the highest noise level above the mean average in the morning due to their location beside road, nature of their daily vocation, and also academic, commercial, and transportation activities had more influence on all these locations. This agrees with Lindawati & Fitriadi (2018); Praveen & Jain (2013) and Henry (2010) who declared location as one of the factors that influence noise pollution, and also commercial, and transportation activity locations are open to more and consistent noise during the day.

### 4.1.2 Mean Noise Level in the Afternoon

The mean noise level in the afternoon is depicted in Figure 4.2. A total of 378 data was collected in the afternoon across all selected locations. The average mean value of noise level in all locations in the afternoon was gotten to be 68.7± 1.87dB. Central Market, Central roundabout are the most noisy with a noise levels above the permissible which are 84.42, 81.92dB. Otolorin, Landmark Chapel, Ile-nla, and Taissa junction are slightly above the average with a value of ± 4.62dB while another location is below the average. Most of the locations above the average are those which fall at the middle of the city, where there are high attentions of shops, markets, and traffic activities. Especially during the Christmas, New Year celebrations and ceremonial activities as at the time the data was taken, population and poor building layout are the causes of high noise pollution exposure during this period of the day. Population, main roads that run through some of these places, traffic noise, and commercial activities, according to *Injaian* *et al*. (2018); Praveen & Jain (2013); Oyedepo & Saadu (2009), are the key sources of environmental noise pollution in the locations that fall inside the city mid-point.

### 4.1.3 Mean Noise Level in the Evening

The mean noise level in the evening is depicted in Figure 4.3. A total of 378 data was collected in the evening across all selected locations. The average mean value of noise level in all locations in the evening was gotten to be 69.53 ± 2.24dB. Central roundabout and central market and Latinwo market are the most noisy with a noise levels above the permissible which are 84.72, 81.28, and 76.14dB respectively. Otolorin, High court Junction, Igangu/Okeki, Ile-Nla, Taissa junction, and Bovas all exceed the average value slightly with a value of ± 3.44dB while another location is still with are below the average. All the location above the average mean value are located beside the road and at the center of the city where there are high commercial activities and high concentrations of traffic volume. The time this data was collected, it was during the festive period and population influenced the ceremonial activities. This agrees with *Meng* *et al*. (2020) that coined that an increase in population and human activities will directly increase the noise pollution of any location.

Fig 4.1: Mean Noise Level in the Morning

Fig 4 .2: Mean noise level in the afternoon

Fig 4.3: Mean Noise Level in the Evening

### 4.1.4 Variation in Noise Exposure during the Day

A total of 1134 data was collected within three weeks across the 21-locations selected in Omu-Aran Township. Statistical Package for Social Science (SPSS) through Harmonic means sample size of Waller Duncana.b at a significant difference (*p <0.05*) gives different variations in noise exposure at each of the selected locations. Table 4.2 shows the average means results with the different (superscripts) significant difference (P-value ), using Harmonic means sample size of Waller Duncana.b. it shows that Central roundabout, Oke-Agbede, Landmark Junction, High Court Junction, Falaye, Ile-Ade, Agamo, Egbe-garage, Otolorin, GRA, Taissa junction, Orolodo, and Taiwo has no significant differences of noise variation in each of the period (morning, afternoon, evening) irrespective of the activities and population involved (this location can be classified as a busy location all through the day). This is because most of these locations are sited along the road with consistent activities, and some fall within the center of the city while some are within the outskirt of the city, where less or no change in activities occurs i.e., low attentions of shops, markets, and less building but with high traffic volume from vehicles and motorcycles horning and friction between the tire and pavement. This is in agreement with what (Injaian et al., 2018); Oyedepo & Saadu (2009) discussed in their research, the most structures that are sited beside the roads are mostly affected by traffic noise pollution. Latinwo market shows that there’s no significant difference in noise exposure in the morning and afternoon, but there’s high exposure in the evening due to the nature of the market having its highest population in the evening period, and also affected by traffic noise due to people returning from work.

Central market, Igangu/Okeki has a significant difference all through the period of the day, but experienced high exposure in the afternoon due to the high population of the market during this period of the day and also traffic volume, conversation and advertisement garget are mostly the sources of noise during this period. Both morning and evening have a slight difference due to population and advertisement garget differences compared to the afternoon. All these reasons are in agreement with what *Meng et al., (2020); Vaccari et.al., (2019)*; Lindawati & Fitriadi (2018); Praveen & Jain, (2013); Adebayo (2013) find out that an increase in population and human activities will directly increase the noise pollution of any location. Bovas, Secretariat, and Landmark Chapel all experienced a high concentration of noise exposure in the morning due to traffic volume, resumption of academic activities for the day, and mostly chapel services during the weeks which are more of music.

Table 4.2: Variation in Noise Exposure during the Day

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| S/N | LOCATION | MEAN NOISE LEVEL FOR EACH PERIOD | | |
| MORNING | AFTERNOON | EVENING |
| 1 | Oke-Agbede | 66.03 ± 7.52a | 68.35 ± 7.31a | 67.91 ± 7.02a |
| 2 | Landmark Junction | 65.20 ± 10.2 a | 64.61 ± 6.20a | 66.55± 7.85a |
| 3 | High Court Junction | 71.41 ± 11.22a | 69.49 ± 6.61a | 72.67 ± 6.25a |
| 4 | Latinwo Market | 70.87 ± 7.27a | 70.44 ± 6.21a | 76.14 ± 6.37b |
| 5 | Falaye | 58.50 ± 4.40a | 59.12 ± 4.79a | 61.05 ± 3.77a |
| 6 | Ile-Nla | 70.59 ± 4.43a | 71.44 ± 3.48ab | 74.23 ± 5.20b |
| 7 | Central Roundabout | 79.11 ± 10.17a | 81.92 ± 8.12a | 84.72 ± 7.89a |
| 8 | Central Market | 78.24 ± 10.63a | 84.42 ± 6.97b | 81.28 ± 6.08ab |
| 9 | Iganngu/ Okeki | 65.21 ± 4.67a | 68.85 ± 5.46b | 72.20 ± 5.72b |
| 10 | Ile-Ade | 64.30 ± 7.04a | 64.00 ± 5.82a | 64.0 ± 3.84a |
| 11 | Agamo | 69.00 ± 4.83a | 67.37 ± 6.26 a | 70.29 ± 5.25 a |
| 12 | Odo-Areyin | 60.00 ± 4.29 a | 63.46 ± 5.45 a | 61.00 ± 6.32 ab |
| 13 | Egbe-Garage | 60.24 ± 6.31 a | 63.73 ± 5.29 a | 62.32 ± 6.00 a |
| 14 | Otolorin | 70.55± 6.24 a | 73.13 ± 9.81 a | 72.87 ± 5.65 a |
| 15 | GRA | 62.91 ± 4.74 a | 61.74 ± 4.94 a | 63.27 ± 6.47a |
| 16 | Bovas | 68.72 ± 6.12 ab | 64.49 ± 10.02 a | 71.64 ± 8.01b |
| 17 | Taissa Junction | 72.94 ± 5.40 a | 71.30 ± 8.45 a | 71.91 ± 5.64 a |
| 18 | Orolodo | 59.40 ± 6.44 a | 62.40 ± 7.27 a | 62.41 ± 5.94 a |
| 19 | Secretariate | 64.50 ± 7.45ab | 69.00 ± 9.38 b | 63.00 ± 5.58 a |
| 20 | Taiwo | 65.00 ± 6.30 a | 63.00 ± 16.69 a | 69.00 ± 6.49 a |
| 21 | Landmark Chapel | 82.5.1 ± 11.40ab | 68.7 ± 4.40a | 72.1 ± 5.10a |

musical instrument for conversation and whispering as concluded by (Meng et al., 2020), while another period of the day has no significant differences.

***Summarily,***

Falaye street is the quietest location in Omu Aran town with an average mean noise level of 59.56 ± 4.40 followed by Odo-Areyin, Egbe-garage, GRA, Orolodo, and Ile-Ade all with the mean noise level of 61.40 ± 6.61 dBA, 61.34 ± 5.56 dBA, 62.10 ± 5.95 dBA, 62.64 ± 5.37 dBA, 64.41 ± 5.63Db respectively.

Oke-Agbede, Landmark Junction, High Court Junction, Ile-Nla, Iganngu/ Okeki, Agamo, Otolorin, Taissa Junction, Taiwo and Secretariate all with a noise level of 72.40± 0.91 dB, 70.43 ± 0.82 dB, 76.16 ± 2.09 dB, 77.13 ± 0.12 dB, 74.42 ± 0.96 dB, 73.70 ± 0.58 dB, 77.19 ± 1.56 dB, 76.86 ± 1.42 dB, 71.80 ± 0.32 dB, 71.10 ± 1.11 dB respectively. All these locations are linear settlement patterns that is affected by flexible pavement, high traffic volume, and other establishments, all this is in agreement with S., & Jain, S. S. (2013) who says the noise of the vehicles increases as the speed of vehicle is increasing.

Central roundabout, Central Market, and Latinwo Market are the nosiest location in Omu-Aran with the mean noise levels of 82.00 ± 8.93 dBA, 81.31 ± 8.37 dBA, 72.49 ± 7.01 dBA, respectively, this is due to commercial and traffic involvement especially horning of vehicle and the awareness the commercial transportation workers made in calling unto their passengers, the increase in noise level was on the rise during the Christmas and New year celebration as at the time this data was collected.Landmark University Chapel with a noise level of 83.16± 2.44 dBA, this is due to educational activities, Religious activities, and the economic activities of the banks in the basement of the structure.

## 4.2 Noise mapping Of Omu-Aran Township

Figure 4.4 shows the mapped locations in Omu-Aran for the level of noise they are unprotected to. Different colors (red, green, yellow, and orange) are used to differentiate the noise levels at each location, the red zone was calibrated between 80-90dB, the light green was calibrated between 60-70 dB, yellow between 71-75 dB, and orange between 76-80 dB. It was observed that only three of the twenty-one (21) locations were within the red zone which is the highest level of noise exposure in the town, Central Market, Central Roundabout, and Landmark Chapel with 87.78 dB, 87.24 dB, and 83.16 dB respectively.

Falaye, Odo-Areyin, Egbe-garage, GRA, Orolodo, and Ile-Ade are in the green zone with the mean noise level of 59.56 ± 4.40, 61.40 ± 6.61 dBA, 61.34 ± 5.56 dBA, 62.10 ± 5.95 dBA, 62.64 ± 5.37 dBA, 64.41 ± 5.63 dBA respectively. Oke- Agbede, Ile-Nla, Iganngu/ Okeki, Agamo, Taiwo and Secretariate all in the yellow zone with a noise level of 72.40± 0.91 dB, 70.43 ± 0.82 dB, 74.42 ± 0.96 dB, 73.70 ± 0.58 dB, 71.80 ± 0.32 dB, 71.10 ± 1.11dB. Landmark Junction, High Court Junction, Otolorin, and Taissa Junction are in the orange zone with the mean noise levels of 76.16 ± 2.09 dB, 77.13 ± 0.12 dB, 77.19 ± 1.56 dB, and 76.86 ± 1.42 dB, respectively.

## 4.3 Evaluating the Health Risk Assessment of noise pollution in Omu-Aran town

The recommended exposure limit and permissible exposure limit equation (REL and PEL) for 8-working hours given by NIOSH, and OSHA also as a standard for both EPA and WHO was used. This REL & PEL are calculated for each location using equations (3.5) and (3.6), while the noise dose was calculated using equations (3.6) and (3.7).

Guest et al., (2018; **WHO (2018);** Fink (2017); Munzel et *al.* (2017), all stated that maximum allowable daily noise dose exposure within 80dB-90dB for 8-working hours is tagged harmful to human health. The result that was calculated shows that the Central roundabout and the central market have 87.24 dB and 86.78dB which exceed the NIOSH Recommended Exposure Limit (REL) of 85 decibels for an 8-hour time-weighted average, but are still within the limit of OSHA Recommended Exposure Limit (REL) of 90dB with 8 working hours exposure. This is due to the location of the streets at the middle of the city, high population, also commercial and transportation engagement at the locations, this agrees to *Meng et al*., (2020) and Adebayo (2013) which says noise pollution increases when there is an increase in population and other human activities. Other locations are all within NIOSH and OSHA occupational standards for 8hrs exposure due to their fewer populations and activities that could result in nuisances as concluded by (*Ganti et al.,* 2011) that the higher the activities and population of any given location the higher the noise pollution exposure. Fig 4.5a and 4.5b show the results of noise dose and Time-Weighted Average (TWA) concerning OSHA and NIOSH.

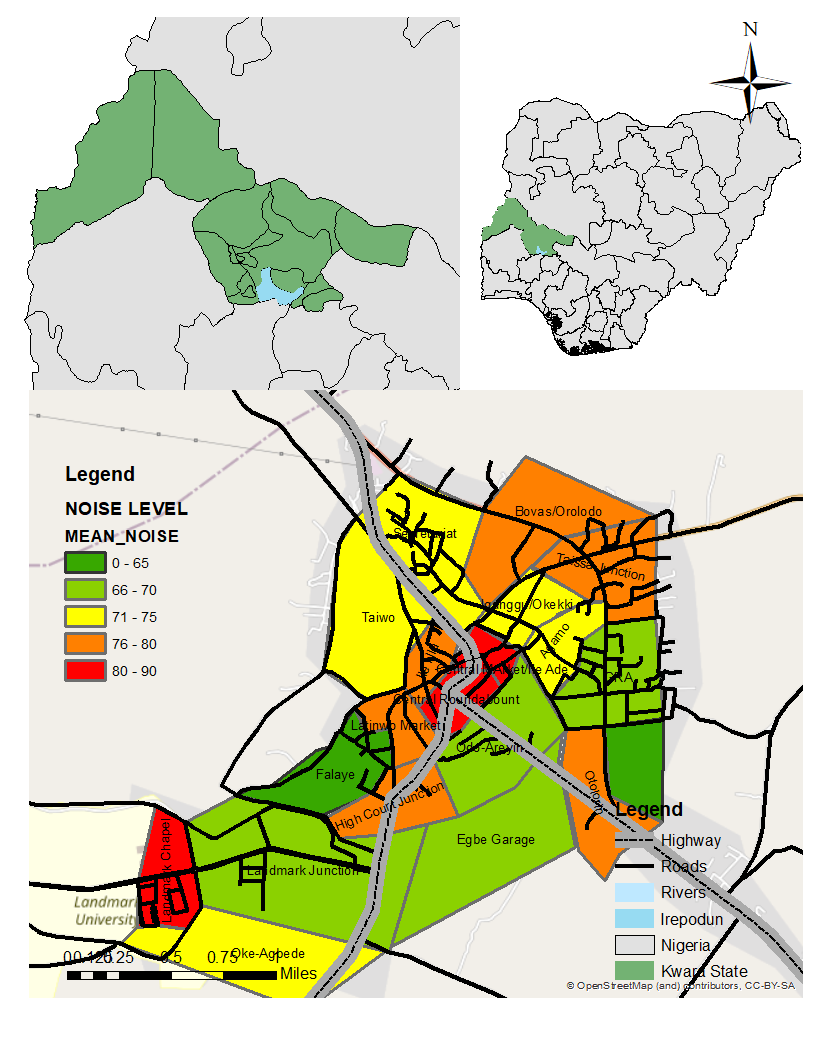


Figure 4.4: Map of Noise Levels in Selected Areas of Omu-Aran Township

Fig 4.5a: Noise Dose Calculated Versus the OSHA &NIOSH Recommended

Fig 4.5b: Time-Weighted Average (TWA) Calculated Versus the OSHA &NIOSH Recommended

## 4.4 Health risk evaluation

Long or frequent exposure to sound exceeding 85 decibels can induce hearing loss, and exposure between 80 and 130 decibels can cause major health problems, according to the American Journal of Public Health (2017). Also, exposure at a frequent rate will have a particular health effect on those that are victims (*Münze et al.,* 2020 and Fyhri & Aasvang, 2010).

Using equation (3.3), the result obtained was used to relate to different categories of noise levels and their consequences as researched by *Ma et al*., (2017). Table 4.3 shows different categories of noise levels and their health consequences based on the exposure at each location. For those residing or working in each of these locations, there’s every tendency that they will be prone to those consequences of noise if not controlled or minimized.

## 4.5 Noise Validation Using ANN

### 4.5.1 Data in ANN

Figure 4.6 shows the uploaded input layers data which comprises 19 associated influential factors which were observed across the selected locations, while Figure 4.7 shows the model summary.

### 4.5.2 Result of the Trained Model

The output layer was trained to give the efficiency of the model in the percentage of accuracy and precision based on the ability of the input data. Scaling of data into X and Y for loss and accuracy visualization of the trained model and plotting of graph to show the model performance. Figure 4.8 shows the model evaluation while figure 4.9a and 4.9b shows the graph that gave a visualized performance of the model after training.

The ANN validation of noise levels in Omu-Aran Township gives one of the best results with 19 associated features of input which showed high performance that gave a prediction accuracy of 97.84%. The root means a square error which is the loss that were given to be (RMSE =0.1096). This was in agreement with Mansourkhaki (2018), neural network gives better validation and also gives the lowest RMSE compared to linear regression The neural network's superior performance is due to its capacity to predict non-linear correlations between sound levels and the factors that influence them.

Table 4.3: The different categories of noise levels and their consequences within Omu-Aran Township

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Location | Categories in Levels | Noise Levels (Db) | Consequence | Source |
| - | 1 | 30-60 | Confusion, discomfort, anger, sleep, etc., disorders | Ising & Kruppa (2004) |
| OROLODO, ILE-ADE, EGBE-GARAGE, ODO-AREYIN, GRA & FALAYE | 2 | 60-75 | annoyance, stress, slight headache, discomfort | *Münze et al*., (2020); *Palamuleni et al*., (2015) ; Ising & Kruppa 2004 |
| OKE-AGBEDE, LANDMARK JUNCTION, HIGH COURT JUNCTION, LATINWO MARKET, ILE-NLA, IGANGU/OKEKI, AGAMO, OTOLORIN, BOVAS, TAISSA JUNCTION, TAIWO & SECRETARIATE | 3 | 75-85 | stress, annoyance, headache, Damage to the ear started or noise-induced hearing loss, ineffective communication | *Basner et al.,* (2014); Abdul-*Majid et.al., (2018);* Anomohanran (2013); (Asonye *et al., (2018)* |
| LANDMARK CHAPEL, | 4 | 85-90 | blood pressure, headache, coronary artery disease | Babisch 2011; Hahad 2019 |
| CENTRAL ROUNDABOUT, CENTRAL MARKET | 5 | 90-120 | cardiovascular effect and increase in physiological responses | Babisch 2011; Munzel *et al.*, (2017); Farooqi *et al*., (2017) ; Zaccheaus *et al.,* (2017) |
| - | 6 | 120 | Internal ear injury is permanent, and balance is compromised | de Beeck et al., (2011); *Hong et al*., (2013) |
| - | 7 | 140 | Significant brain damage | Cernak & Noble-Haeusslein (2010); Basner, (2014) |

Source: Survey 2022

reduce and control noise levels in both urban and semi-urban areas.

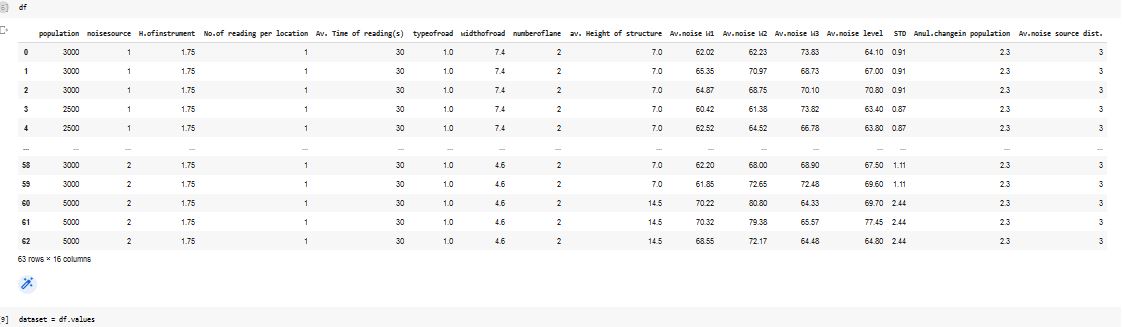


Figure 4.6 Data uploaded for Training

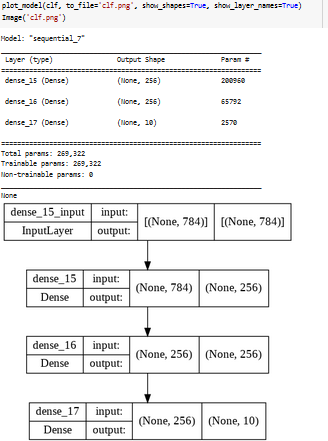


Figure 4.7 Model Summary

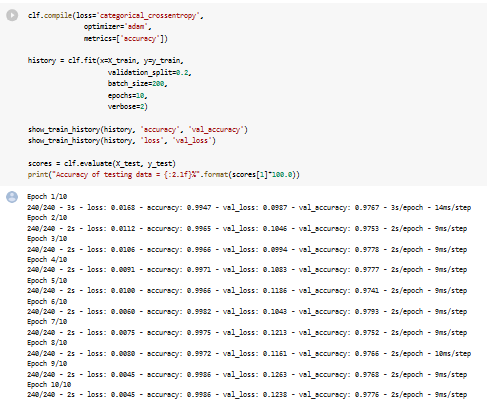


Figure 4.8 Model Evaluation

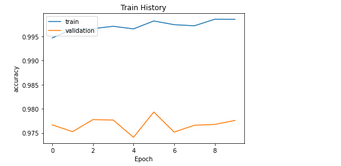


Figure 4.9a Model History showing Percentage of Accuracy

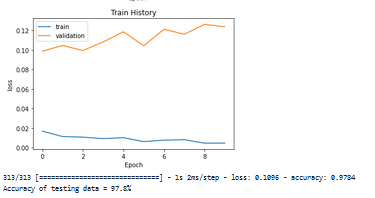


Figure 4.9b Model History showing Percentage of Loss

The study found that the ANN model was accurate at validating Omu-Aran noise levels, which was due to the larger number of input factors, this is in agreement with what Genaro, (2010) says that many Scientists attempted to simulate urban noise, but the results were not as good as expected due to the smaller number of variables in the input, despite the fact that the ANN was able to validate noise with more accuracy. Also, the input variables had a direct impact on noise levels at every location, the higher the influence of these variables in any location the higher the noise level and vice-versa.

Therefore, the validation of Omu-Aran noise levels using ANN gave higher percentage of accuracy, this was an improvement on the ability of the model. Also, the findings had added to the knowledge of researchers, that the model results can help to deduce a preventive measure to control noise pollution as said by Quiñones-Bolaños *et al*. (2016) that noise models are essential tools for developing and applying effective prevention strategies.

## 4.6 Performance Evaluation of Artificial Neural Network in terms of Accuracy and Root Means Square Error (RMSE)

Table 4.4 shows the comparison between different results of noise prediction using Artificial Neural Network in terms of accuracy and root mean square error (RMSE). These differences might be as a result of number of input features, choice of machine learning program (Matlab and Python), number of epochs, and choice in percentage of training and testing data.

Table 4.4: Comparison of Artificial Neural Network Noise Prediction Results

|  |  |  |  |
| --- | --- | --- | --- |
| Author | Title | Accuracy (%) | RMSE |
| (Johar *et al*., 2014) | prediction of bus travel time using ANN: a case study in Dehli | 1.02 | 0.609 |
| Kumar et al., 2012 | A overview of neural networks for traffic prediction | 0.93 | 1.01 |
| (Mansourkhaki *et al.,* 2018) | A neural network noise prediction model for Tehran urban road | 0.9914 | 4.3553 |
| (Das *et al*., 2021) | Prediction of traffic noise induced annoyance: A two-staged SEM-Artificial Neural Network approach | 0.712 | - |
| (Temeng *et al.,* 2021) | Blast-induced noise level prediction model based on Brain Inspired Emotional Neural Network | 0.969 | 1.619 |
| (Elemile *et al*., 2022) | prediction of noise level of Omu-Aran township using artificial neural network | 0.9784 | 0.1096 |

Source: Survey 2022

# CHAPTER FIVE

**CONCLUSIONS AND RECOMMENDATION**

## Conclusion

This work fulfilled the goal of using Artificial Neural Network Model to validate the noise level of Omu-Aran Township. Also, fulfilled the five main objectives: the documentation of the noise levels within the selected locations within the Township; the mapping of the documented noise levels at each location; the health risk evaluation of the documented noise levels; and validation and evaluation of the noise level concerning factors that influence it. At the end of the study the following conclusions were drawn:

1. Population and human activities are the most influential factors that impact the noise level of any location
2. the noise levels increases as the variables increases and vice-versa; both natural and artificial factors enhance the noise exposure of any location
3. the mapping shows that three (3) out of the twenty-one (21) locations are the noisiest in Omu-Aran township
4. any noise levels above 60dB have a health-related effect on humans.
5. there’s is a great rapport between the input data and the output result during the modelling, increase in input data increase the accuracy of the model and vice-versa
6. the modelling confirms the results obtained by the network are 98% accurate. Since the network receives a high number of associated input data.

## Recommendation

From the discoveries and notes during the research, the subsequent are suggested to control and mitigate noise levels of all selected locations.

1. a more detailed study with additional locations and influential factors in Omu-Aran township should be conducted to confirm the noise level
2. physical planning survey should be carried out at each location that was selected for proper control and mitigation. Also, proper planning should be in place for undeveloped areas in Omu-Aran township
3. There should be medical consciousness of the negative effects of noise pollution on the general community.
4. noise pollution will be difficult to control if physical planning and management in semi-urban areas are not properly planned for.
5. More study should be caried out on noise level in Omu-Aran as this study was constraint to time, restricted to some selected locations, and funding.

## 5.3 Contribution to Knowledge

This study had helped to:

1. document the average noise level of selected location in Omu-Aran Township
2. presented the noise exposure level of selected location on a map in other to alert the resident.
3. used higher number of input s of 19 compared to Genaro model in 2010 & 2020 of 15 variables. This gave more acurate value as also suggested by him

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# APPENDIX

**Mean Noise Level in the Morning**

|  |  |
| --- | --- |
| **Location** | **Mean Noise Levels**  **in Omu-Aran** |
| Oke-Agbede | 72.40 |
| Landmark Junction | 70.49 |
| High Court Junction | 76.16 |
| Latinwo Market | 78.06 |
| Falaye | 64.51 |
| Ile-Nla | 77.13 |
| Central Roundabout | 87.24 |
| Central Market | 86.78 |
| Iganngu/ Okeki | 74.42 |
| Ile-Ade | 69.23 |
| Agamo | 73.70 |
| Odo-Areyin | 66.44 |
| Egbe-Garage | 67.07 |
| Otolorin | 77.19 |
| GRA | 67.46 |
| Bovas | 76.86 |
| Taissa Junction | 73.92 |
| Orolodo | 66.38 |
| Secretariate | 71.10 |
| Taiwo | 71.80 |
| Landmark Chapel | 83.16 |

**VARIATION IN NOISE EXPOSURE DURING THE DAY**

|  |  |  |  |
| --- | --- | --- | --- |
| LOCATION | MEAN NOISE LEVEL FOR EACH PERIOD | | |
| MORNING | AFTERNOON | EVENING |
| OKE- AGBEDE | 66.03 ± 7.52a | 68.35 ± 7.31a | 67.91 ± 7.02a |
| LANDMARK JUNCTION | 65.20 ± 10.2 a | 64.61 ± 6.20a | 66.55± 7.85a |
| HIGH COURT JUNCTION | 71.41 ± 11.22a | 69.49 ± 6.61a | 72.67 ± 6.25a |
| LATINWO MARKET | 70.87 ± 7.27a | 70.44 ± 6.21a | 76.14 ± 6.37b |
| FALAYE | 58.50 ± 4.40a | 59.12 ± 4.79a | 61.05 ± 3.77a |
| ILE-NLA | 70.59 ± 4.43a | 71.44 ± 3.48ab | 74.23 ± 5.20b |
| CENTRAL ROUNDABOUT | 79.11 ± 10.17a | 81.92 ± 8.12a | 84.72 ± 7.89a |
| CENTRAL MARKET | 78.24 ± 10.63a | 84.42 ± 6.97b | 81.28 ± 6.08ab |
| IGANNGU/ OKEKI | 65.21 ± 4.67a | 68.85 ± 5.46b | 72.20 ± 5.72b |
| ILE-ADE | 64.30 ± 7.04a | 64.00 ± 5.82a | 64.0 ± 3.84a |
| AGAMO | 69.00 ± 4.83a | 67.37 ± 6.26 a | 70.29 ± 5.25 a |
| ODO-AREYIN | 60.00 ± 4.29 a | 63.46 ± 5.45 a | 61.00 ± 6.32 ab |
| EGBE-GARAGE | 60.24 ± 6.31 a | 63.73 ± 5.29 a | 62.32 ± 6.00 a |
| OTOLORIN | 70.55± 6.24 a | 73.13 ± 9.81 a | 72.87 ± 5.65 a |
| GRA | 62.91 ± 4.74 a | 61.74 ± 4.94 a | 63.27 ± 6.47a |
| BOVAS | 68.72 ± 6.12 ab | 64.49 ± 10.02 a | 71.64 ± 8.01b |
| TAISSA JUNCTION | 72.94 ± 5.40 a | 71.30 ± 8.45 a | 71.91 ± 5.64 a |
| OROLODO | 59.40 ± 6.44 a | 62.40 ± 7.27 a | 62.41 ± 5.94 a |
| SECRETARIATE | 64.50 ± 7.45ab | 69.00 ± 9.38 b | 63.00 ± 5.58 a |
| TAIWO | 65.00 ± 6.30 a | 63.00 ± 16.69 a | 69.00 ± 6.49 a |
| LANDMARK CHAPEL | 82.5.1 ± 11.40ab | 68.7 ± 4.40a | 72.1 ± 5.10a |

**Summary of Noise\_Work.ipynb – Collaboratory**

https://colab.research.google.com/drive/1TJz5K2Ydb4VrsQqDqyoG3ocdJXAucjk-#scrollTo=GaL5NhNeQ3ZT&printMode=true 1/9

import torch

import torchvision

import numpy as np

import matplotlib

import matplotlib.pyplot as plt

import torch.nn as nn

import torch.nn.functional as F

from torchvision.datasets import MNIST

from torchvision.transforms import ToTensor

from torchvision.utils import make\_grid

from torch.utils.data.dataloader import DataLoader

from torch.utils.data import random\_split

%matplotlib inline

# Use a white background for matplotlib figures

matplotlib.rcParams['figure.facecolor'] = '#ffffff'

import pandas as pd

import tensorflow as tf

from tensorflow.keras import datasets, layers, models

import matplotlib.pyplot as plt

import numpy as np

Choose Files No file chosen

Upload widget is only available when the cell has been executed

in the

current browser session. Please rerun this cell to enable.

Saving noise csv to noise csv

from google.colab import files

upload = files.upload()

df = pd.read\_csv('noise.csv')

df

5/4/22, 9:07 AM Noise\_Work.ipynb - Colaboratory

https://colab.research.google.com/drive/1TJz5K2Ydb4VrsQqDqyoG3ocdJXAucjk-#scrollTo=GaL5NhNeQ3ZT&printMode=true 2/9

**population**

**noise**

**source**

**type of**

**road**

**width of**

**road**

**number of**

**lane**

**av. Height of**

**structure**

**noise**

**level**

**0** 3000 1

1.0 7.4

2 7.0 64.10

**1** 3000 1 1.0 7.4

2 7.0

67.00

**2** 3000 1 1.0 7.4 2 7.0 70.80

**3** 2500 1 1.0 7.4 2

7.0 63.40

**4** 2500 1 1.0 7.4 2 7.0 63.80

**...** ...

............ ... ...

**58**

3000 2 1.0

4.6 2 7.0 67.50

**59** 3000 2 1.0

4.62

7.069.60**60** 5000 2 1.0 4.6 2 14.5

69.70**61**5000 2 1.0 4.6 2 14.5 77.45

**62**5000

21.04.6

2 14.5 64.80

63 rows × 7 columns

dataset = df.values

dataset

array([[3.000e+03, 1.000e+00, 1.000e+00, 7.400e+00, 2.000e+00, 7.000e+00,

6.410e+01],

[3.000e+03, 1.000e+00, 1.000e+00, 7.400e+00, 2.000e+00, 7.000e+00,

6.700e+01],

[3.000e+03, 1.000e+00, 1.000e+00, 7.400e+00, 2.000e+00, 7.000e+00,

7.080e+01],

[2.500e+03, 1.000e+00, 1.000e+00, 7.400e+00, 2.000e+00, 7.000e+00,

6.340e+01],

[2.500e+03, 1.000e+00, 1.000e+00, 7.400e+00, 2.000e+00, 7.000e+00,

6.380e+01],

[2.500e+03, 1.000e+00, 1.000e+00, 7.400e+00, 2.000e+00, 7.000e+00,

6.900e+01],

[3.500e+03, 1.000e+00, 1.000e+00, 7.400e+00, 2.000e+00, 9.500e+00,

6.810e+01],

[3.500e+03, 1.000e+00, 1.000e+00, 7.400e+00, 2.000e+00, 9.500e+00,

6.950e+01],

[3.500e+03, 1.000e+00, 1.000e+00, 7.400e+00, 2.000e+00, 9.500e+00,

7.590e+01],

[6.000e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 7.000e+00,

7.190e+01],

[6.000e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 7.000e+00,

7.320e+01],

[3.500e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 7.000e+00,

7.240e+01],

[3.000e+03, 1.000e+00, 5.000e-01, 2.800e+00, 1.000e+00, 7.000e+00,

5.970e+01],

[3.800e+03, 1.000e+00, 5.000e-01, 2.800e+00, 1.000e+00, 7.000e+00,

6.020e+01],

[3.800e+03, 1.000e+00, 5.000e-01, 2.800e+00, 1.000e+00, 7.000e+00,

5.890e+01],

[4.000e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 9.500e+00,

7.060e+01],

[4.000e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 9.500e+00,

7.402e+01],

[4.000e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 9.500e+00,

7.160e+01],

[5.000e+03, 2.000e+00, 1.000e+00, 7.400e+00, 2.000e+00, 9.500e+00,

8.090e+01],

[5.000e+03, 2.000e+00, 1.000e+00, 7.400e+00, 2.000e+00, 9.500e+00,

8.210e+01],

[5.000e+03, 2.000e+00, 1.000e+00, 7.400e+00, 2.000e+00, 9.500e+00,

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8.270e+01],

[7.000e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 9.500e+00,

8.040e+01],

[7.000e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 9.500e+00,

8.330e+01],

[7.000e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 9.500e+00,

8.030e+01],

[4.500e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 9.500e+00,

6.880e+01],

[4.500e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 9.500e+00,

6.770e+01],

[4.500e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 9.500e+00,

6.980e+01],

[3.500e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 9.500e+00,

6.460e+01],

[3.500e+03, 2.000e+00, 1.000e+00, 4.600e+00, 1.000e+00, 9.500e+00,

6.340e+01],

X = dataset[:,0:10]

Y = dataset[:,6]

from sklearn import preprocessing

min\_max\_scaler = preprocessing.MinMaxScaler()

X\_scale = min\_max\_scaler.fit\_transform(X)

X\_scale

array([[0.27272727, 0. , 1. , 1. , 1. ,

0. , 0.21311475],

[0.27272727, 0. , 1. , 1. , 1. ,

0. , 0.33196721],

[0.27272727, 0. , 1. , 1. , 1. ,

0. , 0.48770492],

[0.18181818, 0. , 1. , 1. , 1. ,

0. , 0.18442623],

[0.18181818, 0. , 1. , 1. , 1. ,

0. , 0.20081967],

[0.18181818, 0. , 1. , 1. , 1. ,

0. , 0.41393443],

[0.36363636, 0. , 1. , 1. , 1. ,

0.33333333, 0.37704918],

[0.36363636, 0. , 1. , 1. , 1. ,

0.33333333, 0.43442623],

[0.36363636, 0. , 1. , 1. , 1. ,

0.33333333, 0.69672131],

[0.81818182, 1. , 1. , 0.39130435, 0. ,

0. , 0.53278689],

[0.81818182, 1. , 1. , 0.39130435, 0. ,

0. , 0.58606557],

[0.36363636, 1. , 1. , 0.39130435, 0. ,

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0. , 0.55327869],

[0.27272727, 0. , 0. , 0. , 0. ,

0. , 0.03278689],

[0.41818182, 0. , 0. , 0. , 0. ,

0. , 0.05327869],

[0.41818182, 0. , 0. , 0. , 0. ,

0. , 0. ],

[0.45454545, 1. , 1. , 0.39130435, 0. ,

0.33333333, 0.4795082 ],

[0.45454545, 1. , 1. , 0.39130435, 0. ,

0.33333333, 0.61967213],

[0.45454545, 1. , 1. , 0.39130435, 0. ,

0.33333333, 0.5204918 ],

[0.63636364, 1. , 1. , 1. , 1. ,

0.33333333, 0.90163934],

[0.63636364, 1. , 1. , 1. , 1. ,

0.33333333, 0.95081967],

[0.63636364, 1. , 1. , 1. , 1. ,

0.33333333, 0.97540984],

[1. , 1. , 1. , 0.39130435, 0. ,

0.33333333, 0.88114754],

[1. , 1. , 1. , 0.39130435, 0. ,

0.33333333, 1. ],

[1. , 1. , 1. , 0.39130435, 0. ,

0.33333333, 0.87704918],

[0.54545455, 1. , 1. , 0.39130435, 0. ,

0.33333333, 0.4057377 ],

[0.54545455, 1. , 1. , 0.39130435, 0. ,

0.33333333, 0.36065574],

[0.54545455, 1. , 1. , 0.39130435, 0. ,

0.33333333, 0.44672131],

[0.36363636, 1. , 1. , 0.39130435, 0. ,

0.33333333, 0.23360656],

[0.36363636, 1. , 1. , 0.39130435, 0. ,

0.33333333, 0.18442623],

from

sklearn.model\_selection

import

train\_test\_split

X\_train, X\_val\_and\_test, Y\_train, Y\_val\_and\_test =

train\_test\_split(X\_scale, Y, test\_size=

0.3

X\_val, X\_test, Y\_val, Y\_test = train\_test\_split(X\_

val\_and\_test, Y\_val\_and\_test, test\_size=

0.5

print

(X\_train.shape, X\_val.shape, X\_test.shape, Y\_train

.shape, Y\_val.shape, Y\_test.shape)

(44, 7) (9, 7) (10, 7) (44,) (9,) (10,)

from

keras.models

import

Sequential

from

keras.layers

import

Dense

model = Sequential([

Dense(

32

, activation=

'relu'

, input\_shape=(

10

,)),

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Dense(32, activation='relu'),

Dense(1, activation='sigmoid'),

])

model.compile(optimizer='sgd',

loss='binary\_crossentropy',

metrics=['accuracy'])

Requirement already satisfied: keras in /usr/local/lib/python3.7/dist-packages (2.8.0)

'2.8.0'

!pip install keras --upgrade

import keras

from keras.models import Sequential

from keras.layers import Dense

try:

import pydot

except:

!pip install pydot

try:

import Graphviz

except:

!apt-get install graphviz -y

from keras.utils.vis\_utils import plot\_model

from IPython.display import Image

keras.\_\_version\_\_

# initialize neural network

clf = Sequential()

# first hidden layer for input data

clf.add(Dense(units=64,

kernel\_initializer='uniform',

activation='relu',

input\_dim=X.shape[1]))

# second hidden layer

clf.add(Dense(units=8,

kernel\_initializer='uniform',

activation='relu'))

# the last hidden layer for output

clf.add(Dense(units=1,

kernel\_initializer='uniform',

activation='sigmoid'))

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Model: "sequential\_5"

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Layer (type) Output Shape Param #

=================================================================

dense\_9 (Dense) (None, 64) 512

dense\_10 (Dense) (None, 8) 520

dense\_11 (Dense) (None, 1) 9

=================================================================

Total params: 1,041

Trainable params: 1,041

Non-trainable params: 0

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

None

# compile the network

clf.

compile

(optimizer=

'adam'

,

loss=

'binary\_crossentropy'

,

metrics=[

'accuracy'

])

print

(clf.summary())

plot\_model(clf, to\_file=

'clf.png'

, show\_shapes=

True

, show\_layer\_names=

True

)

Image(

'clf.png'

)

clf = Sequential()

clf add(Dense(units=256

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clf.add(Dense(units=256,

input\_dim=784,

kernel\_initializer='normal',

activation='relu'))

clf.add(Dense(units=256,

input\_dim=64,

kernel\_initializer='normal',

activation='relu'))

clf.add(Dense(units=10,

kernel\_initializer='normal',

activation='softmax'))

print(clf.summary())

plot\_model(clf, to\_file='clf.png', show\_shapes=True, show\_layer\_names=True)

Image('clf.png')

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https://colab.research.google.com/drive/1TJz5K2Ydb4VrsQqDqyoG3ocdJXAucjk-#scrollTo=GaL5NhNeQ3ZT&printMode=true 8/9

Model: "sequential\_7"

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Layer (type) Output Shape Param #

=================================================================

dense\_15 (Dense) (None, 256) 200960

dense\_16 (Dense) (None, 256) 65792

dense\_17 (Dense) (None, 10) 2570

=================================================================

Total params: 269,322

Trainable params: 269,322

Non-trainable params: 0

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

None

clf.compile(loss='categorical\_crossentropy',

optimizer='adam',

metrics=['accuracy'])

history = clf.fit(x=X\_train, y=Y\_train,

validation\_split=0.2,

batch\_size=200,

epochs=10,

verbose=2)

show\_train\_history(history, 'accuracy', 'val\_accuracy')

show\_train\_history(history, 'loss', 'val\_loss')

scores = clf.evaluate(X\_test, y\_test)

print("Accuracy of testing data = {:2.1f}%".format(scores[1]\*100.0))

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Could not connect to the reCAPTCHA service. Please check your internet connection and reload to get a reCAPTCHAchallenge.

Epoch 1/10

240/240 - 3s - loss: 0.0168 - accuracy: 0.9947 - val\_loss: 0.0987 - val\_accuracy: 0.976

Epoch 2/10

240/240 - 2s - loss: 0.0112 - accuracy: 0.9965 - val\_loss: 0.1046 - val\_accuracy: 0.975

Epoch 3/10

240/240 - 2s - loss: 0.0106 - accuracy: 0.9966 - val\_loss: 0.0994 - val\_accuracy: 0.977

Epoch 4/10

240/240 - 2s - loss: 0.0091 - accuracy: 0.9971 - val\_loss: 0.1083 - val\_accuracy: 0.977

Epoch 5/10

240/240 - 2s - loss: 0.0100 - accuracy: 0.9966 - val\_loss: 0.1186 - val\_accuracy: 0.974

Epoch 6/10

240/240 - 2s - loss: 0.0060 - accuracy: 0.9982 - val\_loss: 0.1043 - val\_accuracy: 0.979

Epoch 7/10

240/240 - 2s - loss: 0.0075 - accuracy: 0.9975 - val\_loss: 0.1213 - val\_accuracy: 0.975

Epoch 8/10

240/240 - 2s - loss: 0.0080 - accuracy: 0.9972 - val\_loss: 0.1161 - val\_accuracy: 0.976

Epoch 9/10

240/240 - 2s - loss: 0.0045 - accuracy: 0.9986 - val\_loss: 0.1263 - val\_accuracy: 0.976

Epoch 10/10

240/240 - 2s - loss: 0.0045 - accuracy: 0.9986 - val\_loss: 0.1238 - val\_accuracy: 0.977