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MIGRAINE DETECTION AND ANALYSIS USING FUZZY INTELLIGENT SYSTEM

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Abstract: Fuzzy logic is used to handle situations when the outcome cannot be specified by a hard limit of yes or no. Many human diseases may be diagnosed using a particular test or diagnostic method which tells people whether they have the condition or not. Migraine is a less-known condition; hence, there is no permanent treatment for migraines yet. There isn't a specific test for diagnosing migraines, which implies that only an individual's physical and mental symptoms may be used for the diagnosis of migraines. Symptoms also vary from one another—no standard definition of migraine at the moment. There are currently no tests in the medical field that can diagnose migraines. The symptom indicates the severity and health state of the migraine. This professional method attempts to assess and diagnose migraine utilizing ambiguous symptoms. Obscure refers to items or traits that are not measured using precise logic; in other words, there isn't a significant differentiation between yes and no. Migraine has various symptoms; we can estimate the severity of the migraines based on all these symptoms.

Keywords: Fuzzy Intelligent System, Fuzzy logic, Migraine analysis, Migraine symptom.

Introduction:

Machine learning researchers and practitioners have become part of our everyday and personal affairs. Artificial intelligence includes fuzzy logic. Machine learning is used extensively in every sector of research as well as in non-scientific fields. Machine learning is utilized in diagnostic techniques, medication selection, blood counts, and other sorts of diagnostic tools. Fuzzy logic is a prominent artificial intelligence field. Fuzzy solves problems that cannot be determined utilizing our yes or no, true or false logic. It ranges from 0 to 1, and to express a solution, the membership function is applied. Assume you have a headache. No instrument or procedure can assess or calculate headaches. However, with fuzzy logic, we may decide to use the membership function. We can determine the severity of the headache. We may categorize headaches into mild, moderate, and severe. A conventional fuzzy intelligent system gets fuzzy inputs and interacts with the knowledge base before de-fuzzing files and returning a crisp result. (M, 2018)

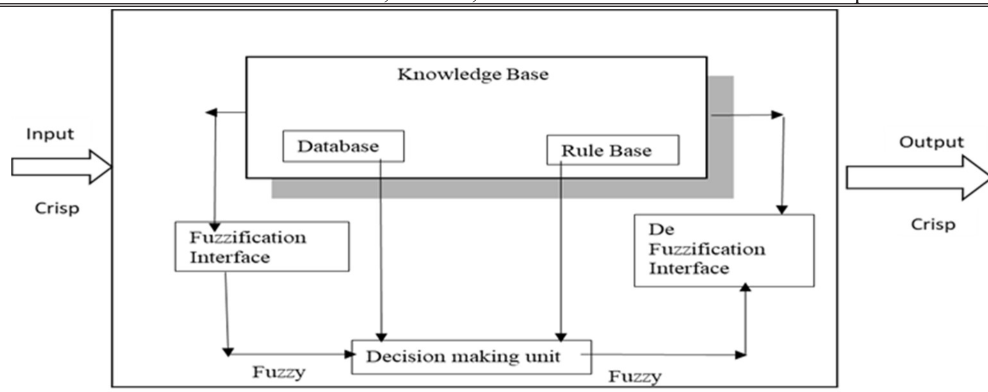


Figure 1: Fuzzy inference system

There are other methods for determining migraine, but we favour fuzzy theory since it is more supple, reliable, and straightforward. Fuzzy theory may also determine whatever can be decided using a typical crisp structure. However, fuzzy cannot be transformed into a crisp using any approach. There seem to be two kinds of implication rules: Mamdani and Sugeno. Mamdani produces Fuzzy output, while Sugenoproduces Crisp output Figure 1. (Friston KJ, 1995)

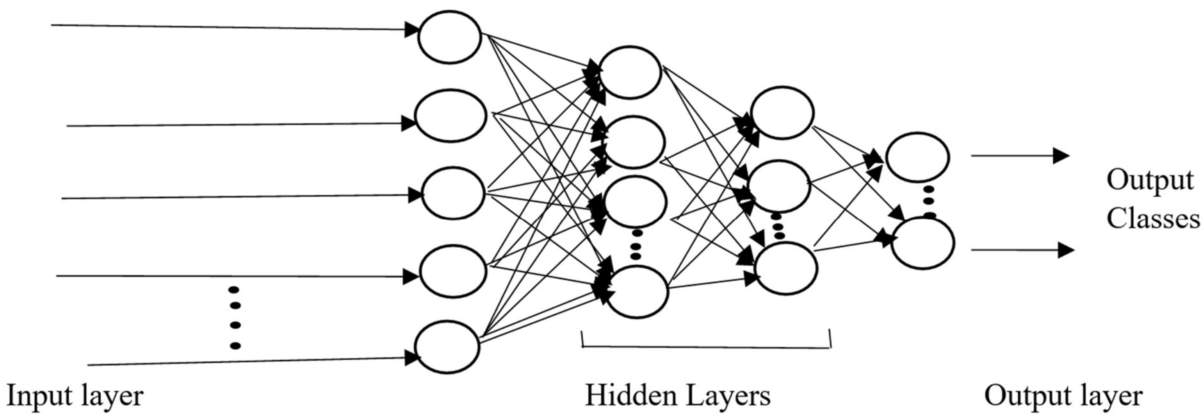
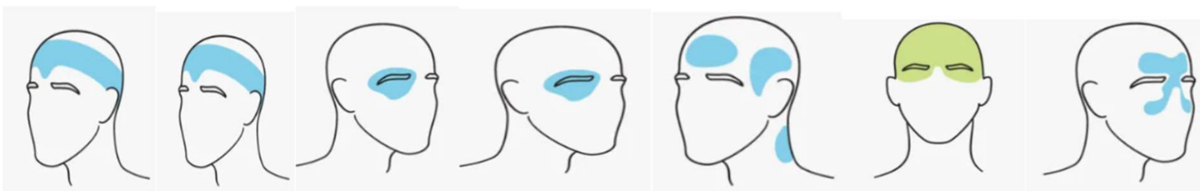


Figure 2: Construction of a multilayer perceptron network

2. Migraine

Migraine is among the most perplexing headaches. Because there is still an understanding of what causes and how migraine operates, there is currently no permanent migraine treatment. Merely symptoms determine if someone gets migraines or not. [R.Narayan 21,22,24,26]Migraine causes intense headaches that can last for a maximum of 72 hours. Pain occurs exclusively in one area or even on one side of the skull. Additional symptom includes frequent urination, while hypersensitivity to light and noise is one of the most crucial in Figure 3. Another indication is nausea and vomiting. If you feel an intense nuisance but still you have no Nausea or Vomiting, an individual probably does not have a migraine. Aura, fuzzy pictures or vision, pulsating pain, pulsing pain, and sleep difficulty are all essential symptoms. One remarkable statistic is that migraines affect over 60% of women, whereas only 30% of males suffer from migraines. (Ashkenazi A Y. I., 2009) Simple analgesics such as aspirin and paracetamol are used in strong doses, but they only diminish rather than cure migraine. Every year, about 70 million hours are due to migraines, and people are unable to work due to the pain's severity. Dry fruit, chocolate, ice cream, and other foods can cause migraines. There are several migraine symptoms; however, we take Headache Intensity, Headache period, Light and sound sensitivity, Nausea, and Vomiting as relevant migraine symptoms. Migraine is a neurological condition. Associated variables for migraine:

1. No migraine
2. Mild
3. Moderate
4. Severe.



1 2 3 4 5 6 7

Figure 3:

1. Tension Headache
2. Migraine
3. Cluster headache
4. Post Traumatic headache
5. Medication overuse
6. Sinus headache

Intelligent system standards and their linguistic variables Headache Intensity Figure 2 (mild, moderate, severe) Headache Duration: No Migraines, Mild, Moderate, Severe Light and sound sensitivity: No effect, Some effect, Huge effect Mild, Moderate, and Severe Vomiting and Nausea (Ashkenazi A, 2009)

3. Headache Severity

There are 3 types of variations:

1.Mild,

2.Moderate, and

3. Severe.

The severity of the headaches is the most crucial symptom of migraine. Migraine headaches are often moderate to severe in severity. According to research, 90% of patients experience severe headaches. (Goadsby PJ, 2017) We used a scale of 0 for no discomfort and 1 for severe agony. Because no measurement really can quantify pain, researchers solve the problem by giving headaches a value between [1,0] as in Figure 4.

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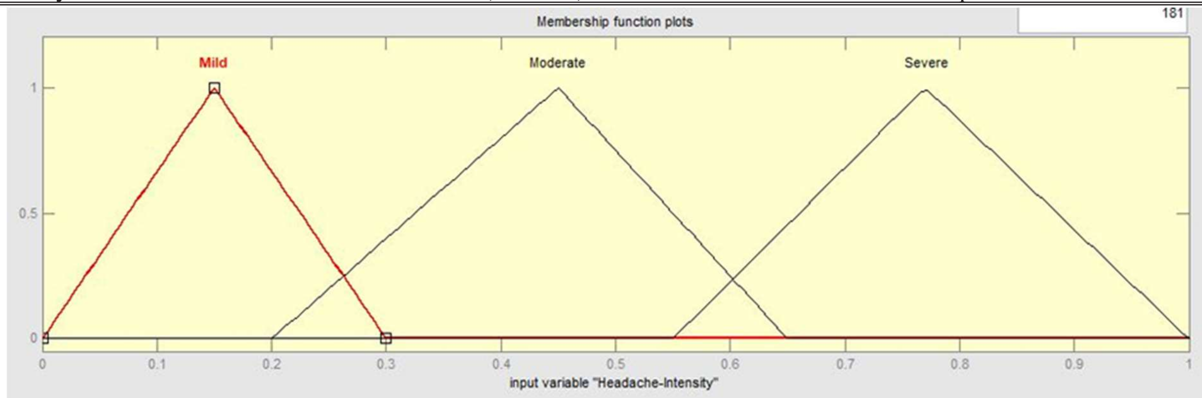

Figure 4: Headache Severity

4. Time Duration of Headache

The time duration of the occurrence of a headache is an essential factor in the diagnosis of migraine. (Burstein R, 2015) If the headache lasts for only for sometimes, it could be a normal headache; if it lasts for 7to 10 hours, it could be a Mild Migraine; if lasts up to whole day, it could be a Moderate Migraine; and if lasts for 3 days, it could be a Severe Migraine and the graphical representation is shown in figure 5. Researchers solve the problem by giving headaches a value between:

1.No migraine 3,0
2. Mild 8, 2
3. Moderate 24, 6
4. Severe 48,72.

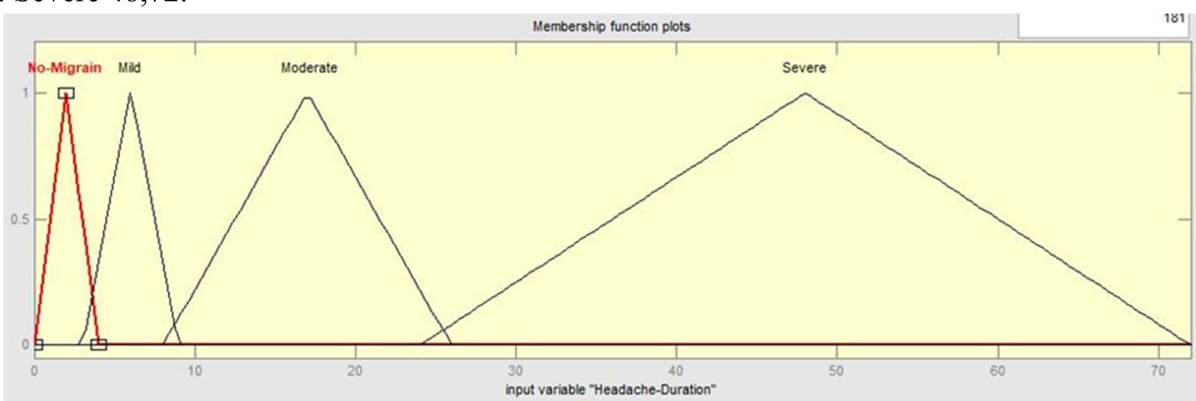

Figure 5: Time Duration of Headache

5. Sensitivity to light and sound

Light and sound sensitivity are present in much more than 90% of instances. People notice blurred light, unfamiliar sounds, and other issues using both sound and light. Because these traits cannot be measured, we have assigned them value as shown in figure 6. (Särkkä S, Dynamic retrospective filtering of physiological noise in BOLD MRI, 2012)

Since these traits cannot be measured, researcher assigned them value.

1. No effect {0, .2}

2. Some effect {.3, .7}
3. Huge effect {.5, 1}

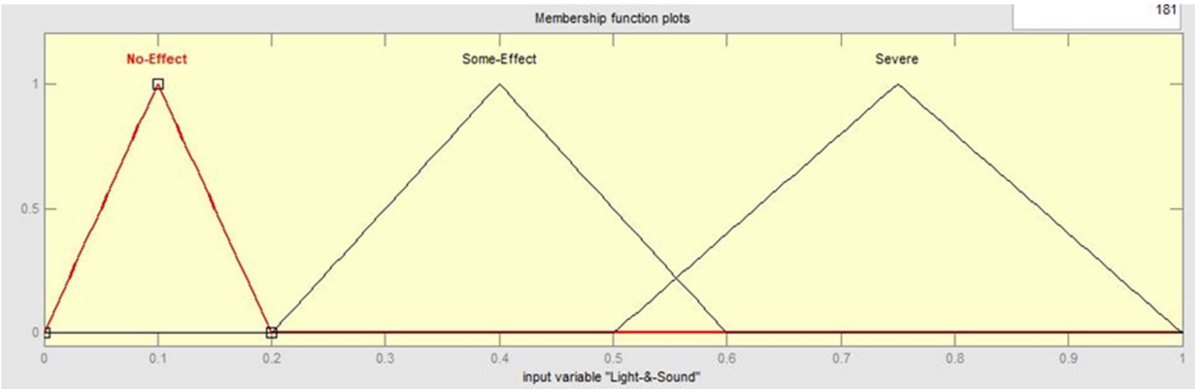

Figure 6:Sensitivity to light and sound

6. Vomiting & Nausea

There are symptoms of nausea and vomiting throughout all migraine instances. If a person does not exhibit this symptom, he or she is not suffering from migraine and the graph is shown below in figure 7. (Friedman DI, 2009)

1. Mild {0, 2}
2. Moderate {1, 4}
3. Severe {2,9}

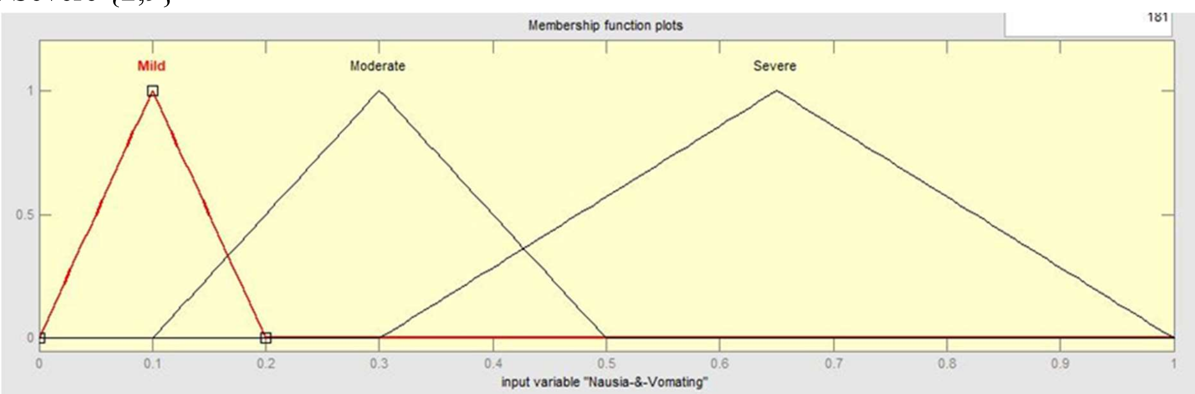

Figure 7: Vomiting & Nausea

7. Procedures

For inferences, we utilised the mamdani style, rule is as follows. (Utiumi MA, 2015)

Table 1: Table 1 shows the early diagnosis and lingual parameters that are used in regulations.	
Early Diagnosis parameter	**Linguistic parameter**
x1= Temperature	No /Yes (0 / 1)
x2= Diplopia	No /Yes (0 / 1)
x3= Convulsion	No /Yes (0 / 1)
x4= Vomiting	No /Yes (0 / 1)

x5= Aura	No /Yes (0 / 1)
x6= Severing by a distinct odour	No /Yes (0 / 1)
x7= Improved with inhalation	No /Yes (0 / 1)
x8= site of headache	Entire head ,One sided, Both sides
x9= Headache severity	Not Throbbing, Throbbing
x10= Intensity of headache	Low, Moderate, Severe, and Extremely Severe
x11= Headache duration	Fewer than 4 hours, 4 hours to 72 hours, 72 hours to 4 weeks, and 4 weeks to months
x12 = Headache history	A few weeks, a few months, and few years
Y =Types of headache	Tension, Migraine Headaches caused by infection, Headaches caused by IICP

IICP – Increased intracranial pressure

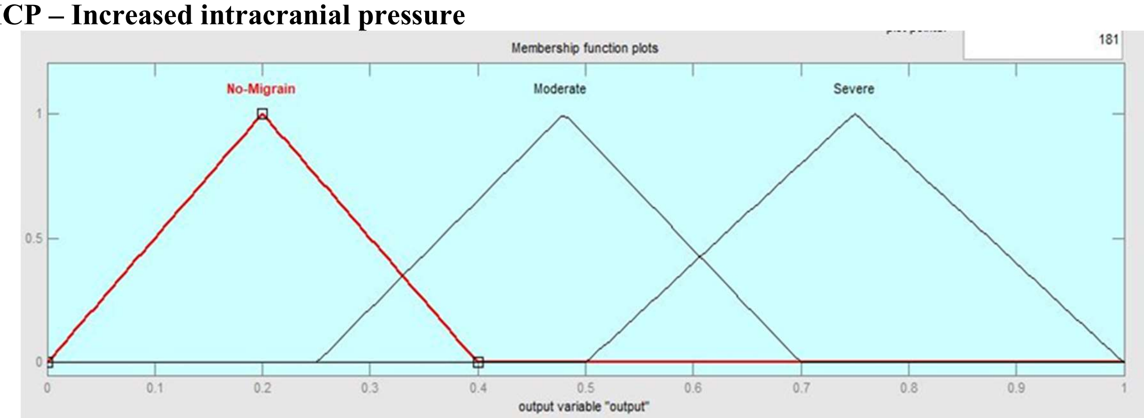

Figure 8: Membership function Plots

a. Nausea &Vomiting vs Headache –Duration:

Here in this section, we observed the effects of nausea and vomiting on headache duration. We found that as the occurrence and duration of nausea and vomiting increases, the possibility of headache duration also increases. [R.Narayan 23,24]When we plot graphs on MATLAB Nausea vomiting vs. Headache –Duration, nausea vomiting is directly proportional to Headache duration as shown in figure 9. As Headache duration increases, nausea and vomiting tendencies also increase. (Särkkä S, 2012)

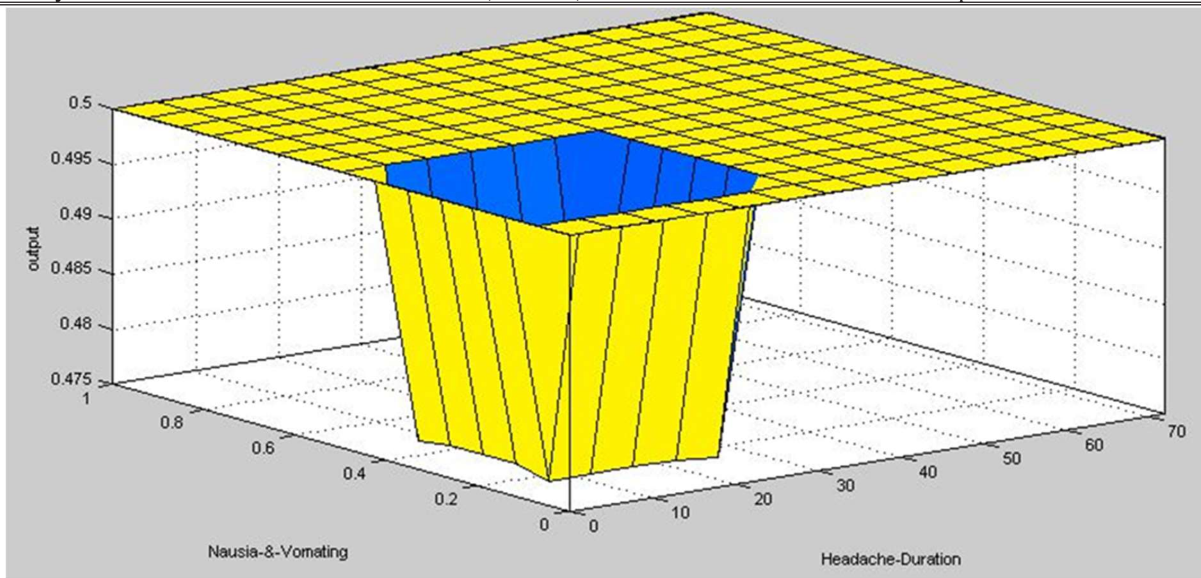

Figure 9:Nausea&Vomiting vs Headache –Duration

b. Light &sound Vs Headache Intensity:

In this section, we investigated the effects of light and sound on headache intensity. We discovered that as the occurrence and duration of Light & Sound increases, so does the possibility of Headache Intensity is also increases. [R.Narayan 25,26]Figure 10 demonstrate the plot graphs of Light & Sound vs Headache Intensity on MATLAB, we see that Light & Sound is directly proportional to Headache Intensity. Light and sound tendencies increase as headache intensity increases. (Meylakh N, 2011)

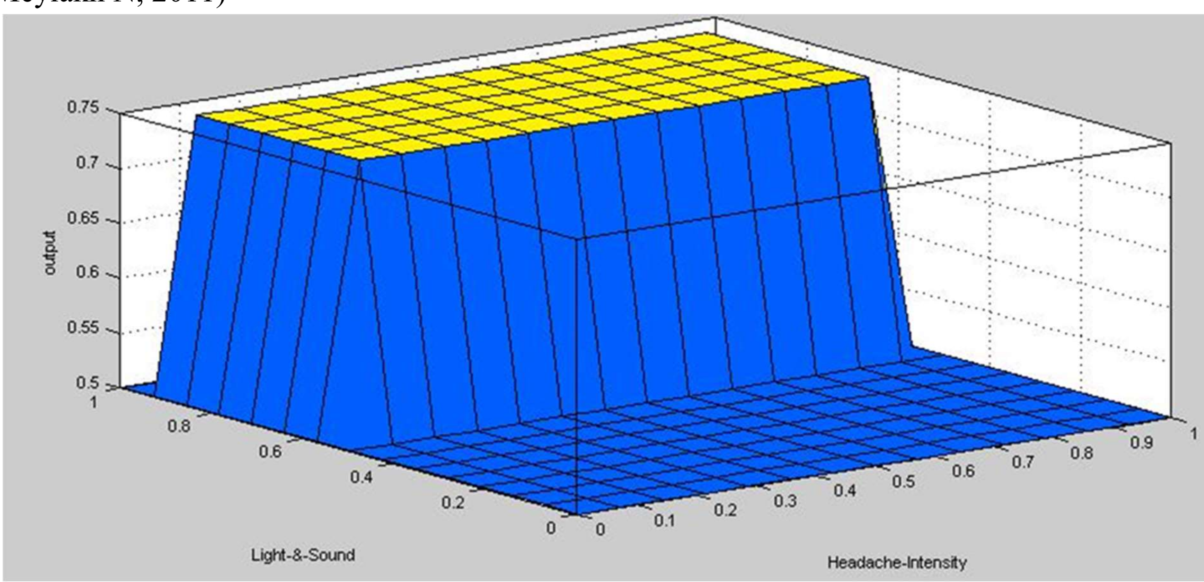

Figure 10: Light &sound Vs Headache Intensity

c. Nausea &Vomiting vs Headache Intensity:

In this section, we looked at how nausea and vomiting affected headache intensity.[R.Narayan27,28] We discovered that as the frequency and duration of nausea and vomiting increase, it increases the possibility of headache intensity. We can see that Light & Sound are directly related to Headache Intensity once we plot graphs of Nausea vomiting vs Headache Intensity on MATLAB. As the intensity of the headache increases, so do the chances of nausea and vomiting as shown in figure 11. (de Tommaso M, 2014)

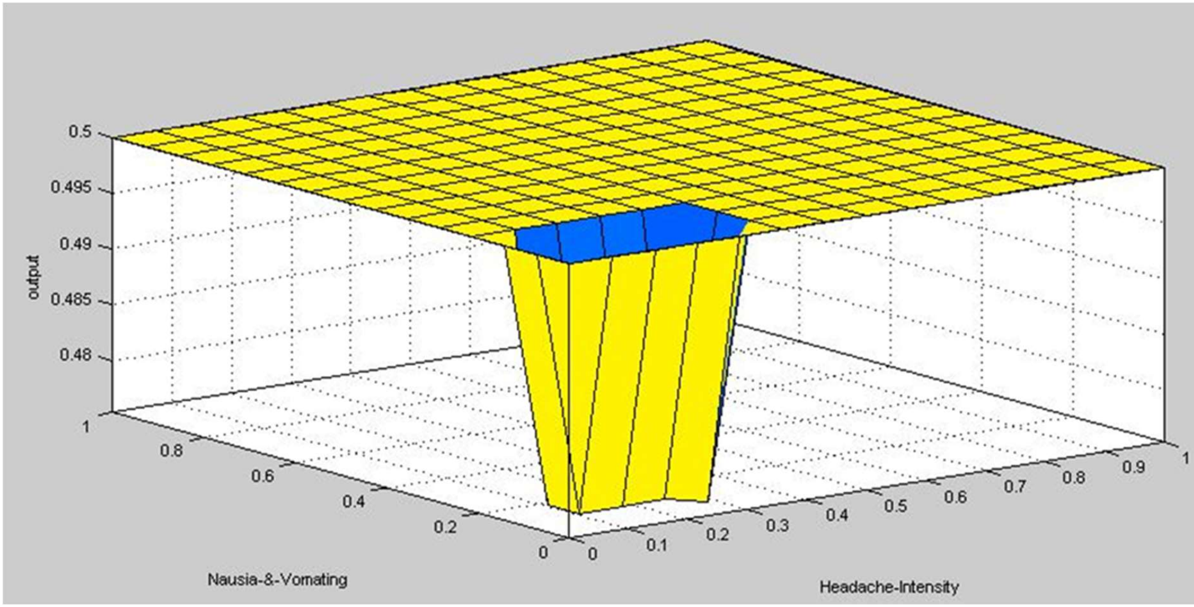

Figure 11:Nausea&Vomiting vs Headache Intensity

We have created two models for analysing the result of the data i.e. Multinomial Logistic Regression and Naïve Bayes. The parameters taken for comparison are TP rate, FP rate, Precision, Recall, F-Measure, MCC and ROC Area. These parameters are described below.

TP rate, also known as True Positive Rate or Sensitivity, is a statistical metric used to measure the proportion of actual positive cases that are correctly identified by a binary classification model. It is calculated as the ratio of true positive predictions to the total number of positive cases, expressed as a percentage.

The formula for TP rate is:

TP rate = (True Positives) / (True Positives + False Negatives)

In other words, TP rate measures the ability of a model to correctly identify positive cases, and is a measure of the model's performance in terms of correctly identifying the class of interest. A higher TP rate indicates that the model is better at identifying positive cases and has fewer false negatives.

FP rate, also known as False Positive Rate or Fall-out, is a statistical metric used to measure the proportion of actual negative cases that are incorrectly classified as positive by a binary classification model. It is calculated as the ratio of false positive predictions to the total number of negative cases, expressed as a percentage.

The formula for FP rate is:

FP rate = (False Positives) / (False Positives + True Negatives)

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In other words, FP rate measures the ability of a model to correctly identify negative cases, and is a measure of the model's performance in terms of correctly identifying the class of non-interest. A higher FP rate indicates that the model is less specific and has more false positives, which means that it may incorrectly classify negative cases as positive.

Precision is a statistical metric used to measure the proportion of true positive predictions among all positive predictions made by a binary classification model. It is calculated as the ratio of true positives to the sum of true positives and false positives, expressed as a percentage.[23,24,33,30]

The formula for precision is:

$$\text{Precision} = (\text{True Positives}) / (\text{True Positives} + \text{False Positives})$$

In other words, precision measures the model's ability to make accurate positive predictions, and is a measure of the model's performance in terms of correctly identifying positive cases while avoiding false positives. A higher precision indicates that the model is better at making accurate positive predictions and has fewer false positives.

Recall is a statistical metric used to measure the proportion of true positive predictions among all actual positive cases in a binary classification model. It is also known as sensitivity or True Positive Rate (TPR). Recall is calculated as the ratio of true positives to the sum of true positives and false negatives, expressed as a percentage.

The formula for recall is:

$$\text{Recall} = (\text{True Positives}) / (\text{True Positives} + \text{False Negatives})$$

In other words, recall measures the model's ability to identify all positive cases correctly, and is a measure of the model's performance in terms of correctly identifying positive cases while avoiding false negatives. A higher recall indicates that the model is better at correctly identifying positive cases, and has fewer false negatives.

F-measure, also known as F1-score, is a statistical metric used to evaluate the performance of a binary classification model. It is a harmonic mean of precision and recall, and provides a single score that balances both measures.

The formula for F-measure is:

$$\text{F-measure} = 2 * (\text{precision} * \text{recall}) / (\text{precision} + \text{recall})$$

In other words, F-measure combines precision and recall by taking their harmonic mean, giving equal weight to both measures. A higher F-measure indicates that the model is better at making accurate positive predictions while avoiding false positives and false negatives.

F-measure is a commonly used metric for binary classification problems, where the goal is to identify positive cases accurately while minimizing false positives and false negatives.

MCC stands for Matthews Correlation Coefficient, and it is a statistical metric used to evaluate the performance of a binary classification model. It measures the correlation between the observed and predicted binary classifications, and takes into account true positive, true negative, false positive, and false negative values. MCC ranges from -1 to +1, where +1 indicates perfect classification, 0 indicates random classification, and -1 indicates total disagreement between observed and predicted classifications.

The formula for MCC is:

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MCC = (TP x TN - FP x FN) / sqrt((TP+FP)(TP+FN)(TN+FP)(TN+FN))

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

In other words, MCC measures the quality of binary classifications, and takes into account all four confusion matrix values. A higher MCC indicates better performance of the classification model.

ROC (Receiver Operating Characteristic) area, also known as AUC (Area Under the Curve), is a statistical metric used to evaluate the performance of a binary classification model. It measures the area under the ROC curve, which plots the true positive rate (TPR) against the false positive rate (FPR) at different classification thresholds.[R.Narayan21,22,31,32]

Table 1: Class wise detailed accuracy (Multinomial Logistic Regression)

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	Class
0.964	0.098	0.941	0.964	0.952	0.872	0.950	Typical aura with migraine
0.983	0.021	0.894	0.983	0.937	0.926	0.970	Migraine without aura
0.667	0.024	0.571	0.667	0.615	0.598	0.841	Basilar-type aura
0.571	0.013	0.615	0.571	0.593	0.579	0.855	Sporadic hemiplegic migraine
0.458	0.016	0.647	0.458	0.537	0.521	0.935	Familial hemiplegic migraine
0.529	0.008	0.750	0.529	0.621	0.617	0.826	Other
0.900	0.000	1.000	0.900	0.947	0.946	0.999	Typical aura without migraine
0.888	**0.066**	**0.883**	**0.888**	**0.883**	**0.830**	**0.941**	

Table 2: Confusion Matrix of Multinomial Logistic Regression

a	b	c	d	e	f	g
238	0	3	1	5	0	0
0	**59**	0	0	0	1	0
2	2	**12**	1	1	0	0
3	1	0	**8**	0	2	0
8	2	3	0	**11**	0	0
1	2	2	3	0	**9**	0
1	0	1	0	0	0	**18**

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a = Typical aura with migraine
b = Migraine without aura
c = Basilar-type aura
d = Sporadic hemiplegic migraine
e = Familial hemiplegic migraine
f = Other
g = Typical aura without migraine

Table 3: Class wise detailed accuracy (Naïve Bayes)

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	Class
0.972	0.085	0.949	0.972	0.960	0.894	0.986	Typical aura with migraine
1.000	0.003	0.984	1.000	0.992	0.990	1.000	Migraine without aura
0.889	0.010	0.800	0.889	0.842	0.836	0.951	Basilar-type aura
0.714	0.008	0.769	0.714	0.741	0.732	0.972	Sporadic hemiplegic migraine
0.542	0.005	0.867	0.542	0.667	0.670	0.986	Familial hemiplegic migraine
0.882	0.008	0.833	0.882	0.857	0.851	0.979	Other
1.000	0.000	1.000	1.000	1.000	1.000	1.000	Typical aura without migraine
0.935	**0.054**	**0.934**	**0.935**	**0.932**	**0.890**	**0.987**	

Table 4: Confusion Matrix of Naïve Bayes

a	b	c	d	e	f	g
240	0	1	3	1	2	0
0	**60**	0	0	0	0	0
0	0	**16**	0	1	1	0
2	0	2	**10**	0	0	0
10	0	1	0	**13**	0	0
1	1	0	0	0	**15**	0
0	0	0	0	0	0	**20**

a = Typical aura with migraine
b = Migraine without aura
c = Basilar-type aura
d = Sporadic hemiplegic migraine
e = Familial hemiplegic migraine
f = Other
g = Typical aura without migraine

Table 5: The comparative analysis of Multinomial Logistic Regression and Naïve Bayes

Multinomial Logistic Regression	Naive Bayes
Correctly classified instances = 88.75%	Correctly Classified Instances = 93.5 %
Kappa statistic = 0.8044	Kappa statistic = 0.8873

8. Conclusion

This intelligent system method is beneficial not only for patients but also for clinicians who treat migraines. This brilliant method employs the most crucial migraine variables and symptoms. MATLAB code was used to develop an intelligent system. We have compare the result obtained from Multinomial Logistic Regression and Naïve Bayes classifier. The result shows the better accuracy of Naïve Bayes classifier (Table 5).

The present study is on migraine patients' mild, moderate, and severe migraine cycles. We observed an increase in connectivity between Headache duration vs. Nausea and vomiting, headache intensity vs. light and sound, and headache intensity vs. Nausea and vomiting over the migraine cycle. Such findings back up the notion that hypersensitivity to specific stimuli and migraines is linked. Furthermore, our findings on migraine headaches support the finding that enhanced sensitivity within one sensory stimulation is linked to greater sensitivity to certain other sensory stimuli, potentially leading to even more chronic migraines.

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Data Availability Statement: The dataset used in this manuscript is made available to users who wanted to build their neural network techniques on a number dataset. This information was gathered from a large number of customers.Dataset is available from public resource and is made available with this article with the link: https://www.kaggle.com/code/jihyeseo/migraine-datasets/data.

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