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Assessment of Thyroid Disorder Prevalence using Fuzzy AHP and Fuzzy TOPSIS Methods

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***Abstract*— This study applies advanced multi-criteria decision making (MCDM technique Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) to analyse the prevalence and symptomatology of various thyroid disorders. The primary objective is to identify the most prominent symptoms and to evaluate the comparative occurrence of hypothyroidism and hyperthyroidism. Using Fuzzy AHP, symptoms were ranked based on expert evaluations, and the analysis revealed that a swollen neck is the most significant and commonly reported symptom among thyroid patients. Subsequently, Fuzzy TOPSIS was employed to assess and compare the prevalence of thyroid conditions, with findings indicating that hypothyroidism is more widespread than hyperthyroidism across the studied population. The integration of fuzzy logic into traditional MCDM methods provides a robust and nuanced framework for handling uncertainty and subjectivity in medical data, offering valuable insights for clinical diagnosis, early detection, and targeted treatment planning of thyroid-related disorders.**

***Index Terms*— Thyroid Disorder, Fuzzy AHP, Fuzzy TOPSIS, MCDM, Hypothyroidism, Hyperthyroidism.**

I. INTRODUCTION

The thyroid gland, a small but critical organ found in the neck, plays an important function in regulating different physiological processes within the human body. Worldwide thyroid diseases are a major public health concern that affect people of all ages and socioeconomic groups. These illnesses cover a wide range of conditions, from hyperthyroidism's hyperactivity to hypothyroidism's hypo activity, all of which have the potential to have detrimental effects on one's health if left untreated. Understanding the incidence of thyroid instances is crucial since it not only clarifies the scope of the issue but also lays the groundwork for developing efficient treatment plans and treatments. Thyroid diseases have been diagnosed at an increasing rate during the last few decades. This increase can be attributed to a number of variables, including enhanced diagnostic tools, raised professional awareness, and altered lifestyle habits.

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While some thyroid disorders can be treated with medicine and lifestyle changes, others may require surgery or continuing medical care, which imposes a significant financial and healthcare burden on both people and societies.

II. Literature Survey

[1] According to ALI KELES and colleagues, detecting thyroid conditions using an expert system they dubbed ESTDD (expert system for thyroid disease diagnosis) s recommended. By utilizing the neuro fuzzy approach, they discovered fuzzy rules that will be incorporated into the ESTDD system. With 95.33 [2] Hui-Ling Chen and colleagues demonstrated a three-stage expert system based on a hybrid support vector machine (SVM) technique to diagnose thyroid-related disorders. In the first step, which is associated with feature selection, endeavours are made to distinguish between different feature subsets with varying degrees of discriminative ability. In the second stage, which changes from feature selection to model development, the acquired feature subsets are input into the designated SVM classifier to train an ideal prediction model, whose parameters are modified via particle swarm optimization (PSO). Finally, the built ideal SVM model performs the duties of thyroid ailment diagnosis using the most prejudiced feature subset and the most beneficial parameters. [3] Clustering approaches were suggested by Ahmad Taher Azar and others to identify thyroid conditions. As far as we are aware, the data set for thyroid illnesses has not yet been subjected to clustering algorithms. In order to determine the ideal number of clusters, this research compares hard and fuzzy clustering techniques for a data set of thyroid illnesses. The performances of the proposed clustering systems are compared using various scalar validity measures. [4] Researchers Amjad Hussain and others have suggested In order to analyze the prevalent Thyroid Disease (TD), which is referred to as a frequent thyroid problem that can cause a variety of ailments, a Multi- layered Fuzzy Mamdani Inference System (ML-MFIS) has been developed. The proposed expert system (TDI- EFL-ES) for diagnosing thyroid illness is based on tests and symptoms. Based on two layers, the Thyroid Disease Identification is Empowered with Fuzzy Logic Expert System. The input variables are displayed on both tiers. Use six input factors in Layer 1 to identify the thyroid condition. Additional tests are then performed in Layer II to identify the disease type, either hyperthyroidism or hypothyroidism.[5] In this research, Tahir Alyas and colleagues compare the performance of various machine learning methods, including decision trees, random forests, KNNs, and artificial neural networks, on the dataset in order to more accurately predict the disease given the parameters derived from the dataset. The dataset has also been altered to allow for precise classification prediction. For better dataset comparability, the classification was carried out on both sampled and unsampled datasets. [6] Ritesh Jah, The study utilizes dimension reduction techniques and data augmentation to improve thyroid disease prediction accuracy, achieving a remarkable 99.95%. This high accuracy demonstrates the effectiveness of these methods but also highlights potential challenges such as increased computational complexity and data integrity issues. While dimension reduction can lead to loss of information and data augmentation requires significant resources, the approach offers a significant advancement in predictive performance for thyroid disorders. [7] Haneet Kour Shivastuti, Jatinder Manhas, Vinod Sharma., Support Vector Machine (SVM) offers excellent precision but can be computationally costly for large datasets; it reached 93% accuracy in identifying thyroid problems. Random Forest (RF) achieved 92% accuracy, offering resilience and interpretability; nevertheless, as the number of trees increases, it may become less effective when dealing with very large datasets and consume more resources. While both approaches work well for diagnosing thyroid disorders, SVM performed marginally better in our investigation. Support Vector Machine (SVM) offers excellent precision but can be computationally costly for large datasets; it reached 93% accuracy in identifying thyroid problems. With 92% accuracy, Random Forest (RF) offers resilience and interpretability, but as the number of trees increases, it may become less efficient with very large datasets and require more resources. [8] Borzouei., When it came to identifying thyroid diseases, neural networks outperformed multinomial logistic regression with a mean accuracy of 96.3% as opposed to 91.4% for the latter. Neural networks are very efficient, but they need a lot of computing power and big datasets. Even though it's simpler, neural networks may be better at capturing complicated patterns than logistic regression.[9] Priyanka Duggal., Thyroid disease diagnosis accuracy was 92.92% when Support Vector Machine (SVM) and Recursive Feature Elimination (RFE) were used. SVM requires fine-tuning and can be computationally demanding, despite its effectiveness. Even though Recursive Feature Elimination is helpful for selecting features, it can take a while when working with big datasets. [10] Saeed M Bafaraj., The study evaluated the efficacy of nuclear medicine, CT scans, and MRI in the diagnosis of thyroid diseases. MRI showed better specificity (22.22%) and sensitivity (38.8%) than CT scans, which had great specificity (71.42%) and sensitivity (70.96%). Notwithstanding its benefits, MRI's poorer sensitivity and specificity may occasionally limit its applicability. Despite their effectiveness, CT scans include

radiation exposure, which has dangers and may limit its application. The study demonstrates that, in spite of its practical drawbacks, MRI provides superior diagnostic performance over other approaches. Recent works have emphasized the role of artificial intelligence and decision-making frameworks in thyroid disorder analysis. Hu et al. [1] and Raza et al. [2] demonstrated machine learning's effectiveness in analyzing thyroid function from laboratory data. For imaging, Cao et al. [3] and Xu et al. [4] reviewed deep learning applications in thyroid ultrasound, while Yao et al. [8] proposed a multimodal transformer model integrating clinical and imaging data. Explainable AI approaches, such as those by Sutradhar et al. [9], highlight the importance of transparency in clinical decision support. Furthermore, fuzzy logic-based frameworks like those applied by Alharbi et al. [11] and Do et al. [12] show that hybrid AHP–TOPSIS systems can effectively evaluate complex medical criteria under uncertainty.

III. METHODOLOGY

A. Analytical hierarchical process (AHP)

The fuzzy AHP method simply sets the AHP scale to the scale of the fuzzy triangle for which priority is to be available.

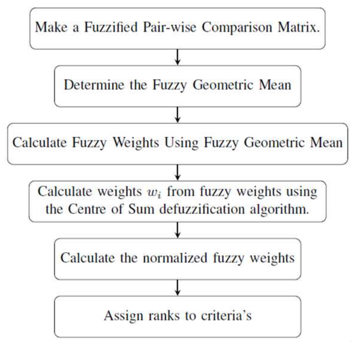

Figure 1. Hierarchical structure of the Methodology

Step 1. Formulation a Fuzzy-AHP Saaty's Scale with linguistic terms

$$Z_{ij} = \sum_{k=1}^{n} \frac{Z_{kij}}{k} \tag{1}$$

Step 2: The paired input matrix in accordance with the average preference, as illustrated in the Equation 2.

TABLE I: FUZZY AHP

Classic Satty's Scale	Linguistic terms	Fuzzy Scale
1	Equally significant	(1,1,1)
3	Weakly significant	(2,3,4)
5	Fairly significant	(4,5,6)
7	Strongly significant	(6,7,8)
9	Absolutely significant	(9,9,9)

$$P = \begin{bmatrix} Z_{11} & Z_{12} & \cdots & Z_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ Z_{n1} & Z_{n2} & \cdots & Z_{nn} \end{bmatrix} \tag{2}$$

Where: *P* represents the pairwise contribution matrix.
Step 3: The fuzzy comparison values' geometric mean. Here's what Buckley (1985) estimates is going on in equation 3.

$$t_i = \left(\prod_{j=1}^{n} Z_j \right)^{\frac{1}{n}}, \quad i = 1, 2, \ldots, n \tag{3}$$

Where:
t_i = geometric mean of fuzzy comparison values,
$\prod_{j=1}^{n} Z_j$ = product of each fuzzy value from the pairwise comparison matrix.

Step 4: The Fuzzy Weights of each Criterion
This is illustrated in Equation (4) with the following three sub-steps:
Step 4.1: Find each of their vector sums.
Step 4.2: Find the power (−1) of the vector sum. Replace the fuzzy triangular number in ascending order.
Step 4.3: Find the fuzzy weight of a criterion.

$$w_i = t_i (t_1 \oplus t_2 \oplus \cdots \oplus t_n)^{-1} = \{eW_i, fW_i, gW_i\} \quad (4)$$

Where: eW_i, fW_i, gW_i are the obtained fuzzy triangular numbers.
Step 5: Since W_i are always fuzzy triangular numbers, they must be defuzzified using the fuzzy Centre of Area (COA) method. This method is proposed by Chou and Chang (2008) using Equation (5).

$$M_i = \frac{eW_i + fW_i + gW_i}{3} \quad (5)$$

Where: M_i represents a non-fuzzy number.
Step 6: Normalization of Fuzzy Weights
Now, M_i computed outside of Equation (6) is a non-fuzzy number but needs to be normalized according to Equation (7).

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \quad (6)$$

Where: N_i represents the final weights after normalization.
These six steps are followed to determine the normalized weights for the criteria and sub-criteria. Then the scores for each sub-criterion are calculated by multiplying the weight of each sub-criterion by its associated criterion. Based on these results, the sub-criteria with the highest scores are suggested to the decision maker.

TABLE II. CRITERIA FOR ASSESSMENT BY USING FUZZY – AHP TRIANGULAR SCALE

	BW	SC	ITW	MC	F	BoM	SN
BW	(1,1,1)	(2,3,4)	(1,2,3)	(4,5,6)	(2,3,4)	(6,7,8)	(0.11,0.11,0.11)
SC	(0.25,0.33,0.5)	(1,1,1)	(0.12,0.14,0.16)	(0.11,0.12,0.14)	(0.12,0.14,0.16)	(3,4,5)	(1,2,3)
ITW	(0.33,0.5,1)	(6,7,8)	(1,1,1)	(0.14,0.16,0.2)	(6,7,8)	(5,6,7)	(2,3,4)
MC	(0.16,0.2,0.25)	(7,8,9)	(5,6,7)	(1,1,1)	(4,5,6)	(2,3,4)	(0.12,0.14,0.16)
F	(0.25,0.33,0.5)	(6,7,8)	(0.12,0.14,0.16)	(0.16,0.2,0.25)	(1,1,1)	(3,4,5)	(0.11,0.12,0.14)
BoM	(0.12,0.14,0.16)	(0.25,0.33,0.5)	(0.14,0.16,0.2)	(0.25,0.33,0.5)	(0.2,0.25,0.33)	(1,1,1)	(0.11,0.11,0.11)
SN	(9,9,9)	(0.33,0.5,1)	(0.25,0.33,0.5)	(6,7,8)	(7,8,9)	(9,9,9)	(1,1,1)

The next step suggested by the methodology is to find the fuzzy geometric mean of the data values. This is calculated using Equation 4 and is shown in Table III.

TABLE III: A FUZZY GEOMETRIC MEAN VALUE FOR EACH CRITERION

Criterion	Fuzzy General Values	Label
BW	(1.40, 1.83, 2.21)	r1
SC	(0.38, 0.48, 0.60)	r2
ITW	(1.49, 1.84, 2.32)	r3
MC	(1.27, 1.54, 1.80)	r4
F	(0.51, 0.61, 0.73)	r5
BoM	(0.21, 0.24, 0.29)	r6
SN	(2.24, 2.57, 3.13)	r7

We obtained fuzzy-weights by completing the sub-steps of step 4, and they are shown in Table X.

TABLE IV: FUZZY WEIGHTS FOR EACH CRITERION

ri	Weights (Fuzzy Triangular Numbers)
r1	(0.26, 0.20, 0.29)
r2	(0.34, 0.05, 0.08)
r3	(1.34, 0.20, 0.30)
r4	(1.14, 0.17, 0.23)
r5	(0.46, 0.07, 0.09)
r6	(0.19, 0.03, 0.04)
r7	(2.02, 0.28, 0.41)

The mean field approach must result in fuzzy triangular numbers for the W_i calculated in Table X to be accurate. Equation 6 is used for this, and the table below displays the non-fuzzy numbers.

TABLE V: NON-FUZZY WEIGHTS FOR EACH CRITERION

ri	Wi
r1	0.25
r2	0.16
r3	0.61
r4	0.51
r5	0.21
r6	0.09
r7	0.90

B. Fuzzy TOPSIS

TOPSIS is based on the notion that the chosen alternative should be geometrically closest to the fuzzy positive ideal solution (FPIS) and farthest from the fuzzy negative ideal solution (FNIS).

TABLE VI: LINGUISTIC VARIABLES FOR EACH CRITERION'S IMPORTANCE WEIGHT

Linguistic variables	Triangular fuzzy weights
Very low (VL)	(0,0,0.2)
Low (L)	(0.2,0.3,0.4)
Medium (M)	(0.4,0.5,0.6)
High (H)	(0.6,0.7,0.8)
Very high (VH)	(0.8,1,1)

This makes TOPSIS especially useful for decision-making problems that involve trade-offs between conflicting criteria. In addition, the fuzzy extension of TOPSIS takes into account uncertainty and imprecision in human judgment.

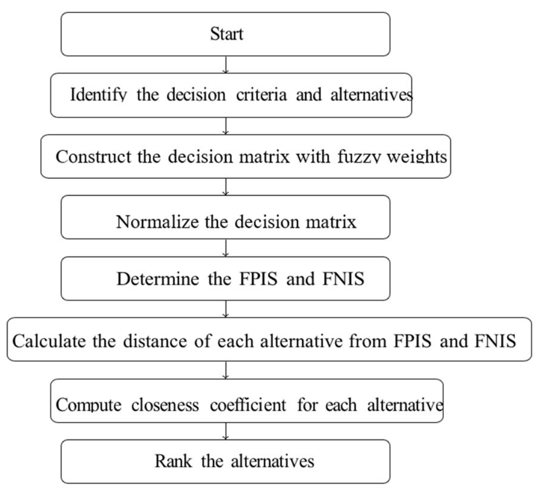

Figure 2. Flowchart of Fuzzy TOPSIS Methodology

TABLE VII: CRITERIA IMPORTANCE WEIGHTED BY THREE DECISION-MAKERS

CRITERIAS	D1	D2	D3
BW	H	H	VH
SC	M	M	H
ITW	H	VH	H
MC	M	H	H
F	H	H	VH
BoM	H	L	M
SN	VH	VH	VH

Where: *A1* is Hyperthyroidism, *A2* is Hypothyroidism and *A3* is Normal Thyroid Gland

$C_iA_i = (\min\{a_k\}, \text{avg}\{b_k\}, \max\{c_k\})$ where $k = (1,2,...,n)$ & $i = (1,2,...,n)$. Similarly, weights are calculated using the above formula with reference to table VII. Here each value is divided by 10 to normalize.

TABLE VIII: LINGUISTIC FACTORS FOR RANKING

LINGUISTIC FACTORS	TRIANGULAR FUZZY NO.
Very less relevant (VLR)	(0,0,2)
Less relevant (LR)	(2,3,4)
Relevant (R)	(4,5,6)
Highly relevant (HR)	(6,7,8)
Very highly relevant (VHR)	(8,9,10)

TABLE IX: DECISION-MAKERS' RATINGS OF THE THREE POSSIBILITIES BASED ON FIVE CRITERIA

CRITERIA / ALTERNATIVE		DECISION-MAKERS		
		D1	D2	D3
C1	A1	VLR	VLR	LR
	A2	VHR	VHR	HR
	A3	R	R	LR
C2	A1	VHR	VHR	VHR
	A2	VLR	VLR	LR
	A3	R	LR	R
C3	A1	LR	LR	VLR
	A2	HR	HR	VHR
	A3	R	R	HR
C4	A1	VHR	VHR	HR
	A2	HR	HR	VHR
	A3	R	R	LR
C5	A1	HR	HR	VHR
	A2	VHR	VHR	HR
	A3	LR	LR	VLR
C6	A1	LR	LR	VLR
	A2	HR	HR	VHR
	A3	LR	LR	R
C7	A1	VHR	VHR	VHR
	A2	VHR	VHR	VHR
	A3	VLR	VLR	VLR

TABLE X: FUZZY WEIGHTS FOR THE THREE ALTERNATIVES AND A FUZZY DECISION MATRIX

	A1	A2	A3	WEIGHTS
C1	(0,1,4)	(6,8.3,10)	(2,4.3,6)	(.4,.5,.6)
C2	(6,8.3,10)	(0,1,4)	(2,4.3,6)	(.1,.2,.3)
C3	(0,2,4)	(6,7.6,10)	(4,5.6,8)	(.7,.8,.9)
C4	(6,8.3,10)	(6,7.6,10)	(2,4.3,6)	(.5,.65,.8)
C5	(6,7.6,10)	(6,8.3,10)	(0,2,4)	(.2,.35,.5)
C6	(0,2,4)	(6,7.6,10)	(2,3.6,6)	(0,0,.2)
C7	(8,9,10)	(8,9,10)	(0,0,2)	(.8,1,1)

TABLE XI: NORMALIZED FUZZY DECISION MATRIX

	A1	A2	A3
C1	(0.00, 0.10, 0.40)	(0.60, 0.80, 1.00)	(0.20, 0.40, 0.60)
C2	(0.60, 0.80, 1.00)	(0.00, 0.10, 0.40)	(0.20, 0.40, 0.60)
C3	(0.00, 0.20, 0.40)	(0.60, 0.76, 1.00)	(0.40, 0.60, 0.80)
C4	(0.60, 0.80, 1.00)	(0.60, 0.80, 1.00)	(0.20, 0.40, 0.60)
C5	(0.60, 0.80, 1.00)	(0.60, 0.80, 1.00)	(0.00, 0.20, 0.40)
C6	(0.00, 0.20, 0.40)	(0.60, 0.80, 1.00)	(0.20, 0.40, 0.60)
C7	(0.80, 0.90, 1.00)	(0.80, 0.90, 1.00)	(0.00, 0.00, 0.20)

TABLE XIII: DISTANCES BETWEEN EACH CRITERION AND A^* WITH REGARD TO A_i

	C1	C2	C3	C4	C5	C6	C7
$d(A_1,A*)$	0.51	0.19	0.73	0.33	0.25	0.22	0.22
$d(A_2,A*)$	0.24	0.26	0.31	0.33	0.25	0.22	0.22
$d(A_3,A*)$	0.34	0.22	0.44	0.54	0.42	0.17	0.94

(i = 1,2,&3). Where $A*$ is maximum value of C_i

TABLE XIV DISTANCES BETWEEN EACH CRITERION AND A^- WITH REGARD TO A_i (I = 1,2,3) WHERE A^- IS MINIMUM VALUE OF C_i

	C1	C2	C3	C4	C5	C6	C7
$d(A_1,A^-)$	0.14	0.19	0.23	0.48	0.34	0.05	0.86
$d(A_2,A^-)$	0.44	0.07	0.64	0.48	0.34	0.11	0.86
$d(A_3,A^-)$	0.24	0.11	0.52	0.24	0.17	0.06	0.12

$$D(A_i, A^\wedge) = \left[\frac{1}{3}\sum(A^\wedge - A_i)^2\right]^{1/2}$$

where ∧ is ∗ for A∗ & − for A−.

IV. RESULTS

A. FUZZY AHP

We can observe swollen neck is given the highest rank followed by intolerance to weather, menstrual cycle, body weight, fatigue, sleep cycle and bowel movement respectively.

TABLE XV

	FUZZY W$_i$	W$_i$	NORMALIZED	RANK
BW	(0.26, 0.20, 0.29)	0.25	0.09	4
SC	(0.34, 0.05, 0.08)	0.16	0.06	6
ITW	(1.34, 0.20, 0.30)	0.61	0.22	2
MC	(1.14, 0.17, 0.23)	0.51	0.19	3
F	(0.46, 0.07, 0.09)	0.21	0.08	5
BoW	(0.19, 0.03, 0.04)	0.09	0.03	7
SN	(2.02, 0.28, 0.41)	0.90	0.33	1
		Σ2.73	Σ1	

B. Fuzzy TOPSIS

TABLE XVI

	A1	A2	A3
d∗	2.45	1.82	3.06
d−	2.29	2.95	1.46
CCi	0.48	0.62	0.91

$$_i = \frac{d_i}{d_i^* + d_i^-}$$

where I = (1, 2, . . . , N) A3 > A2 > A1

Which clearly states that cases of normal thyroid are more. We can say 62% of reports are from hypothyroidism and 48% from hyperthyroidism The results show that Swollen Neck obtained the highest normalized weight (0.33), indicating it as the strongest indicator of thyroid dysfunction.

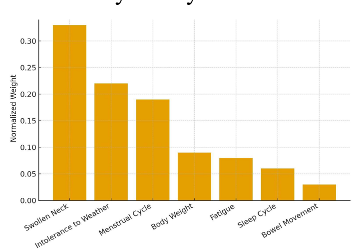

Figure 3. Symptom Significance Ranking

Intolerance to Weather (0.22) and Menstrual Cycle irregularities (0.19) followed. In contrast, Bowel Movement issues (0.03) and Sleep Cycle disturbances (0.06) received lower weights. These results align with clinical understanding that goitre is a highly specific symptom, while bowel and sleep issues are less specific.

C. Fuzzy TOPSIS

The closeness coefficients were: Normal Thyroid (0.91), Hypothyroidism (0.62), and Hyperthyroidism (0.48). This indicates that the majority of individuals have normal thyroid function, while hypothyroidism is more prevalent than hyperthyroidism. The higher prevalence of hypothyroidism is consistent with literature identifying iodine deficiency, autoimmune disorders, and aging as contributing factors.

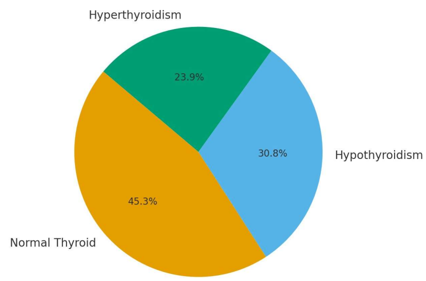

Figure 4. Distribution of Thyroid Conditions

V. CONCLUSION

Using the Fuzzy Analytic Hierarchy Process (AHP) to discover common thyroid symptoms is a beneficial strategy that takes into account the relative relevance of various symptoms and provides for a more nuanced view of the illness. The emergence of common symptoms such as swollen neck, intolerance to weather, and menstrual cycle irregularities reflects the complexities of thyroid problems and their different clinical presentations. These results emphasize the value of a thorough and multifaceted approach to thyroid illness diagnosis. The presence of additional symptoms, the results of any laboratory tests, and the patient's medical history should all be taken into account by healthcare professionals when evaluating patients who present with a combination of these symptoms for thyroid dysfunction. This will help them make accurate and timely diagnoses and treatment decisions. The use of the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) has provided us with useful insights into the prevalence of thyroid illnesses, with a special focus on the distribution of cases of normal thyroid gland, hypothyroidism, and hyperthyroidism. Our thorough examination of the data yielded some remarkable results and implications. First and foremost, the fact that the incidence of normal thyroid gland instances is higher than that of hypothyroidism and hyperthyroidism highlights the overall health and wellbeing of a substantial section of the population under research. This promising feature of thyroid health demonstrates the effectiveness of public health programs, awareness campaigns, and healthcare interventions focused at increasing thyroid health and early identification. In comparison of hypothyroidism and hyperthyroidism cases of hypothyroidism were found to be more prevalent. For a variety of reasons, including both biological and environmental ones, hypothyroidism is more common than hyperthyroidism. Some of the contributing factors for hypothyroidism are aging, iodine deficiency, autoimmune disorders, diet and lifestyles etc.

Although genetic and other environmental variables may also contribute to the development of hyperthyroidism, their overall prevalence is smaller than that of those linked to hypothyroidism. It's important to remember that both disorders can be managed with medication, dietary changes, and, occasionally, surgery or radiation therapy. Early detection and treatment are essential for sustaining thyroid health.

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