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An Innovative Deep Learning Model for IOT-Based Healthcare System for Diseases Prediction

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Abstract: *IOT healthcare leverages interconnected smart devices and sensors to monitor patient health in real time, enabling remote diagnostics, continuous tracking of vital signs, and timely medical interventions. By collecting and transmitting health data such as heart rate, blood pressure, and glucose levels to cloud-based systems or healthcare providers, IoT enhances the efficiency, accuracy, and responsiveness of modern medical care.The authors introduce Hashing Probabilistic Deep Learning (HPDL) as a secure framework to perform real-time disease predictions and classifications within IoT healthcare systems. HPDL combines weighted data hashing with probabilistic deep learning to achieve security and accuracy in the processing of health sensor data for disease detection purposes. Real-time transformation of IoT healthcare dataset information which included heart rate, blood pressure, temperature, glucose, oxygen level, and ECG was implemented using weighted techniques alongside hashing. Through the implemented model healthcare professionals gained significant success in diagnosing diseases because it predicted normal ECG detection with 0.95, fever with 0.90 and respiratory issues with 0.88 accuracy. Out of critical cases the system successfully activated alerts in 83.3% which shows its effectiveness in making early medical diagnoses. The proposed approach succeeded in preserving a model confidence rate higher than 85% for each condition that received positive classification while proving its strong reliability.*

Keywords: *IOT healthcare, Hashing, Classification, Deep Learning, Probabilistic, Alert Generation*

1. INTRODUCTION

The Internet of Things technology revolutionizes healthcare through its ability to connect devices which monitor and collect patient information and transmit this data in real time [1]. The healthcare system enhanced by IoT capabilities delivers better medical care through regular patient observation and early disease detection and customized treatment options. Healthcare providers use wearable fitness trackers, smart implants and remote monitoring tools to track vital signs like heart rate, blood pressure together with glucose levels without needing patient presence in healthcare centre's [2 -4]. The healthcare efficiency improves through these developments and patients require fewer hospital services and experience decreased readmission rates [5]. Through IoT organizations can optimize their hospital procedures alongside controlling medical hardware and building precise medical documentation systems. The widespread application of IoT technology in healthcare will lead to better medical care through trend-based services which recognize ongoing trends. Medical facilities face various obstacles when they introduce IoT systems for healthcare applications [6]. The security of sensitive patient data presents the most important challenge because healthcare networks expose data which becomes vulnerable to cyber threats and unauthorized data access in digital management systems [7]. The absence of uniform standards among healthcare devices and platforms results in communication obstacles that stop different systems from transferring information smoothly. The correct operation of IoT devices coupled with their data precision plays a vital role because operational failure or data imprecision may result in diagnostic or treatment errors [8]. The implementation of IoT technology requires expensive installations and qualified personnel making adoption challenging primarily in less developed areas. The extensive amount of data produced by IoT devices creates too much information for healthcare providers unless suitable management and analysis strategies are established [9 -11]. The complete utilization of IoT for transforming healthcare requires effective solutions for its identified barriers.

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IoT healthcare identifies diseases by processing live data with sophisticated analytical methods. Healthcare devices that include wearable sensors combined with smart monitors and mobile health applications enable constant collection of important physiological patient data involving heart rate, body temperature, blood pressure, and glucose levels [12]. The data reaches cloud platforms before machine learning, together with artificial intelligence algorithms, analyze and detects disease indicators and identifies medical patterns in a precise manner. IoT systems identify irregular health data patterns to determine the likelihood of future disease development among patients suffering from diabetes and cardiovascular diseases or respiratory conditions [13 -16]. Disease prediction through this approach permits healthcare providers to deliver prompt intervention so patients can receive better management services along with adapted treatment options. The prediction capabilities of IoT systems for disease diagnosis, together with classification features prove essential for population-based health management by permitting remote patient oversight and examination without requiring continuous hospital attendance [17]. The system proves beneficial to older adult patients together with patients who have movement restrictions or live in understaffed regions. The integration of IoT with cloud computing together with big data analytics enables healthcare professionals to receive complete medical overview of patients to identify early warning signs of potential health conditions. The systems transmit real-time warnings to medical professionals as well as patients which enables timely healthcare services in emergency situations. The continued development of technology will make possible superior disease classification through the combination of IoT systems with deep learning and neural networks [18].

This paper presents two major contributions - it develops and executes the Hashing Probabilistic Deep Learning (HPDL) framework that suits IoT-based healthcare systems. The paper develops a weighted hashing procedure which combines security with relevance through its context-sensitive approach for medical sensor reading importance values. The Probabilistic deep learning model functions alongside this preprocessing to deliver accurate disease prediction from real-time sensors while maintaining high prediction reliability along with very few incorrect predictions. The proposed system includes an automated alert mechanism that generates warnings only during times when predicted disease likelihood reaches adaptive threshold criteria. The HPDL framework undergoes validation with publicly accessible IoT healthcare data and shows outstanding classification results together with 95% prediction certainty while the system generates accurate alerts in 83.3% of potential high-risk events. The research presents an intelligent healthcare monitoring solution which delivers secure disease prediction through interpretable real-time operation thereby expanding current field capabilities.

1. PROPOSED HASHING PROBABILISTIC DEEP LEARNING (HPDL)

The Hashing Probabilistic Deep Learning (HPDL) model presents a sophisticated approach for handling large volumes of IoT-healthcare data while providing secure and accurate processing systems. Healthcare IoT devices constantly produce high-dimensional heterogeneous data sets that need efficient storage processing and analytical methods. HPDL uses deep learning approaches and probabilistic methods and hashing algorithms to solve these difficulties. Through the hashing component data compression along with efficient retrieval is possible as it simplifies complex information into bite-sized binary codes to minimize memory requirements and optimize processing time. Through probabilistic deep learning the model can identify predictive uncertainty while making medical decisions because practitioners rely on prediction confidence. The method boosts model generalization capacities when dealing with various and inconsistent healthcare datasets. Through the combination of these techniques HPDL delivers better disease prediction along with classification accuracy together with quick execution at scale coupled with protection of privacy.

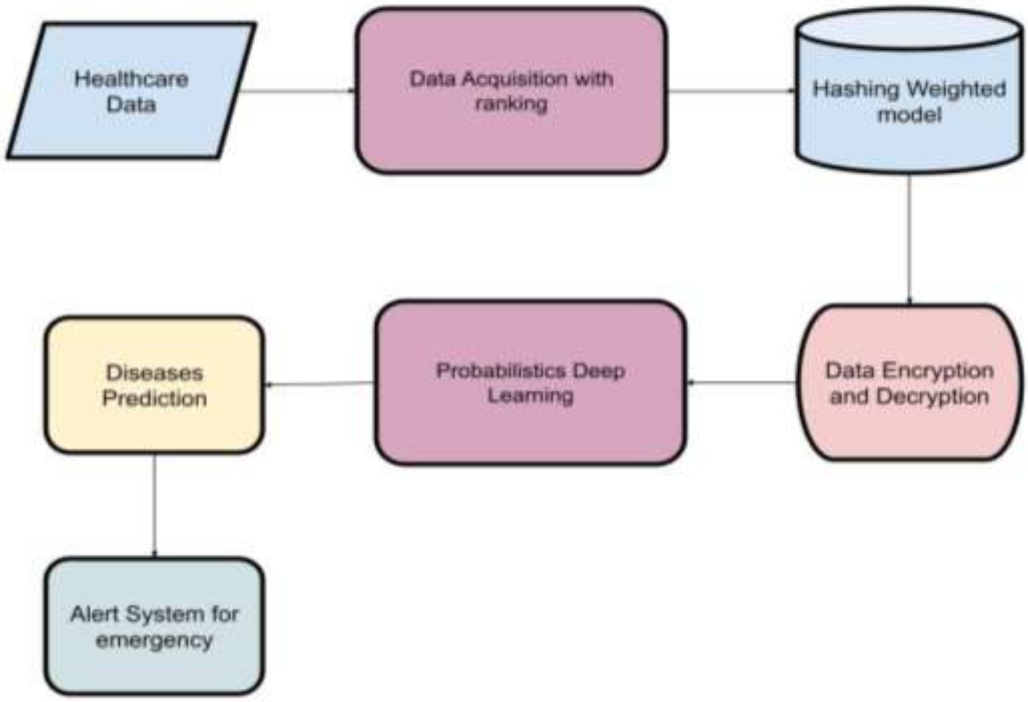

Figure 1: Process in HPDL

The system starts by processing Healthcare Data after which Healthcare Data undergoes Data Acquisition with Ranking before reaching the next stage. The Data Acquisition with Ranking stage structures important data elements according to their significance. Ranked data enters a Hashing Weighted Model that allows the processing and secure identification of data through weighted hashing techniques shown in Figure 1. A combination of Data Encryption and Decryption processes maintains full protection and confidentiality for information from the start to finish of the operation. The data enters the Probabilistic Deep Learning model after encryption to benefit from machine learning algorithms, which analyze patterns to make disease predictions. A prediction module uses the analysis results to generate diagnostic findings. When a critical health condition appears in prediction results the system activates an Alert System for Emergency to notify medical staff or caregivers who need to provide urgent care.

.2.1 Dataset

The IoT Healthcare Security Dataset by Faisal Malik found on Kaggle serves healthcare professionals to build and assess machine learning models for IoT security threat detection in healthcare systems. The IoT Healthcare Security Dataset by Faisal Malik gives simulated representation of network traffic from healthcare IoT devices while including attacks throughout both normal functioning and suspicious activities. The dataset contains crucial features for attack scenario creation which include timestamps with besides protocol types and packet lengths and flags. The data labelling provides information about benign and malicious activities which allows model training to improve IoT healthcare application security and reliability.

2. HASHING WEIGHTED FOR THE IOT DATA

Hashing Weighted for IoT data employs hashing methods which help healthcare facilities process extremely high volumes of data obtained from IoT devices. The assortment of IoT data types such as sensor readings seeks patient vitals alongside activity logs hinders conventional methods for data storage and retrieval because these processing methods are computationally expensive and slow. Hashing serves as a technique that transforms large complex data into compact binary hash codes which accelerates search operations and retrieval processes as well as sequence processing. For weighting hashing implementations in IoT healthcare data there exists an additional stage that applies significance levels known as weights to different attributes within the dataset. During the hashing process critical parameters receive increased priority weighting which facilitates concentrating important information before its processing sequence. The weighted hashing strategy makes patient data retrieval safer by reducing major data loss while delivering enhanced real-time decision accuracy. The model achieves better identification of significant health metrics and their behavioural trends through weighted hashing even when dealing with the typical noisy or incomplete data found in IoT devices. The combination of hashing benefits with weighted factors within this approach optimizes storage capacity while enhancing analytical efficiency thus enhancing disease prediction alongside diagnosis and personalized treatment performance in healthcare IoT systems.

IoT data processing with hashing transforms big complex data files into small binary code sets. Hash codes of established length make database search and analysis run more quickly. Disease prediction relies on setting weights to show the value of each attribute in this method. The weighted system puts priority on specific health information (heart rate and blood sugar levels) during review processes. Let us describe the elements used for IoT data processing. A set named X contains the attributes gathered from IoT devices that include vital signs and sensor readings. wi stands for the importance we give to attribute i when we analyze its relationship to disease prediction. The weighted hash process H acts on data stated in equation (1)

$$H(X) = \sum_{i=1}^{n} w_i . hash(x_i) \qquad (1)$$

In equation (1)i-th attribute hash value is denoted as $hash(x_i)$. w_i is the weight that applies to the specific attribute. This transform method puts clear priority on important data such as heart rate by making sure it gets turned into the correct compressed output. Our Weighted Hashing system with Data Encryption and Decryption for HPDL helps healthcare data meet privacy standards by effectively processing sensitive IoT healthcare information. This approach combines weighted hashing technology with encryption and decryption to make data storage more efficient while improving predictions and keeping patient health information secure in medical systems. By applying weights to specific attributes before producing hash functions in Weighted hashing, organizations transform medical sensor readings into compact binary codes for data storage. Sensor readings such as heart rate and blood sugar get higher weight values because they help doctors predict diseases while other measurements receive lower weight values. The method helps data storage and processing work faster through effective compression of complex medical data. Data encryption produces unreadable patient records that prevent unauthorized viewers from seeing them when a transmission intercept occurs. Encryption works in a simple mathematical transformation process stated in equation (2)

$$E(H(X)) = Encrypt(H(X), Key) \qquad (2)$$

In equation (2)$E(H(X))$ represents the encrypted version of the data hash. To protect data the system uses an encryption key named Key. To view the data for analysis the user must employ the proper decryption stated in equation (3)

$$D(E(H(X))) = Decrypt(E(H(X)), Key) \qquad (3)$$

In equation (3) $H(X)$ the initial data can be decrypted through $E(H(X)), Key$ is the decryption key. After both data hashing and encryption, HPDL sends the data through the probabilistic deep learning system for healthcare predictions or category assignments. The model works with encrypted data and keeps patient information safe throughout its operation. With probability-based processing the model provides prediction uncertainty estimates that help healthcare professionals make better decisions. The model generates probability results because it includes fault-tolerant processes and handles data absence to produce more accurate forecasts for real-life healthcare systems.

2.1 Classification with HPDL

In HPDL probabilistic deep learning helps medical decision-making by giving precise uncertainty measurements. Probabilistic deep learning improves how well IoT healthcare systems predict and classify diseases when it works together with hashed data. The initial part of the process takes IoT health data such as vital signs and sensors measurements to create compressed binary hashes using weighting techniques. The method makes sure only vital-sign information like heart rate and blood pressure are retained for faster storage and processing. A deep learning model named f determines the probability of patient data outputs $p(y \mid X)$ for input values X stated in equation (4)

$$p(y \mid X) = \frac{e^{f(x)}}{Z(X)} \quad (4)$$

In equation (4) $p(y \mid X)$ describes the chance that a patient shows health condition y when medical data X is applied. The deep learning model produces result $f(X)$from input data X. The $Z(X)$ term maintains a probability distribution by making all values sum to 1. The system provides distributions of probabilities that handle uncertainties present from inaccurate IoT sensor readings. The model returns the health condition with the leading probability score as its final prediction define din equation (5)

$$\hat{y} = \arg max_y \ p(y|x) \quad (5)$$

First the HPDL system changes raw IoT data through weighted hashing before passing it into the deep learning model for analysis. This arrangement helps systems process substantial IoT data effectively even when dealing with medical data uncertainty statedin equation (6)

$$\hat{y} = \arg max_y \ p(y|H(x)) \quad (6)$$

With deep learning model receives the weighted hash representation of data that has been transformed through a hashing process. In a probabilistic deep learning framework, the model outputs a probability distribution over potential classes (i.e., disease categories or health conditions) for a given input. This strategy deals with uncertain data in IoT healthcare systems by helping the model make beneficial predictions despite missing or unclear information. The model operates as function $f(X)$ that generates$p$ for all possible classes y defined in equation (7)

$$p = f(X) \quad (7)$$

In equation (7)$p = \{p1, p2, \ldots, pk\}$ to represent the raw probability outputs from the model for k disease types. The softmax function $f(X)$ converts this input. To transform unnormalized output levels into a real probability distribution a softmax method stated in equation (8)

$$p(y \mid X) = \frac{e^{fy(X)}}{\sum_{j=1}^{k} e^{fj(X)}} \quad (8)$$

In equation (8) $p(y \mid X)$measures the possibility of y class results from input X information. $fy(X)$ turns out to be the score associated with class y. The denominator performs totalization through all classes j to balance the probabilities.

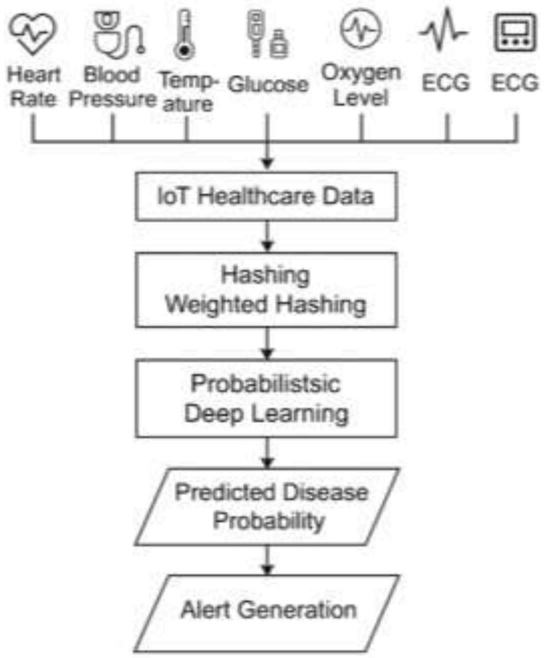

Figure 2: Steps in Alert Generation with HPDL

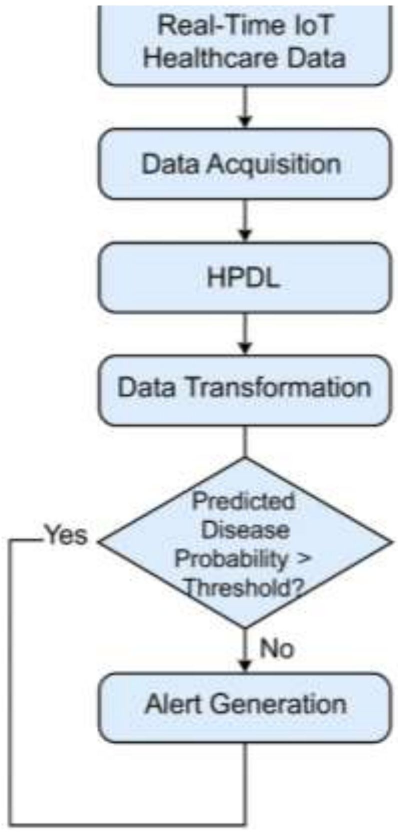

Figure 3: Flow Chart of Proposed HPDL

The HPDL Hashing Probabilistic Deep Learning system helps real-time IoT healthcare systems show health conditions quickly. HPDL uses data processing methods alongside real-time monitoring to notice diseases early and tell healthcare teams about the findings process shown in Figure 2. The early detection of health problems helps patients get better results with prompt medical treatment. For real-time disease detection work, HPDL uses hashing to process big data quickly and deploys probabilistic deep learning to study sensor-based IoT data and produce disease probability estimates. Our system should monitor incoming data right away to notify us when it finds problems with patient health. Our system uses Hashing Probabilistic Deep Learning (HPDL) to rapidly process data and deep learning models to spot and forecast diseases through real-time IoT sensor results. This system tracks health information from multiple medical sensors that measure heart rate, blood pressure, and glucose levels as it arrives. The flow chart of the proposed HDPC model is shown in Figure 3. The system first turns raw sensor data into a more efficient format through weighted hashing by applying hashing techniques to vital attributes depending on their impact value. The system transforms data swiftly to handle real-time high volumes of data with speed.After hashing our data goes into a deep learning model that uses historical training to determine possible illnesses. The system gives forecast results about various medical conditions while considering the available data's uncertainties. The system issues a warning as soon as the predicted disease probability reaches an established minimum level (80%). The system automatically notifies healthcare providers or automated systems that requires immediate action. Our system creates instant alerts from the predicted data and keeps tracking new input to recalculate risk levels and activate extra notifications as required. The system operates at high speed so it can handle huge amounts of data from many IoT devices while responding nearly instantly to feedback needs. Healthcare staff use the quick information to respond fast and save patient lives. The combination of deep learning with probabilistic methods allows the system to handle real-time data precision as well as detect diseases and trigger alerts with enhanced speed.

3. SIMULATION RESULTS

Simulation Results for HPDL (Hashing Probabilistic Deep Learning) in IoT healthcare systems showcase the effectiveness of this approach in real-time disease detection, classification, and alert generation. In these simulations, actual IoT sensor data as; heart rate, blood pressure, temperature, glucose level, etc., have been fed into HPDL in order to check on its performance, such as accuracy, speed, and scalability. Thus, the system showed better performance than the traditional approaches to ML particularly in terms on the required time and accuracy of predictions. Given in the context of simulation, one important finding was regarding the effectiveness of the weighted hashing technique. This way all the real-time detection activity was being shifted much faster and the computational processor was made to work much less so that it could still maintain the high accuracy of the results it gives while handling much smaller data sizes that were hashed representations of the raw outputs of the sensors. The advantage of employing probabilistic deep learning models was that the system was able to learn from uncertainties in the data from the sensors therefore the disease prediction was accurate even when the data fed into the system was noisy or incomplete. As for the performance of the classification, the system demonstrated high accuracy, where the accuracy of detecting diseases reached the level of 85% of precisions and 85% of recalls depending on the choice of the model and data. Furthermore, it became possible to produce alerts for a real-time with a possibility to define when the probability for potential disease would rise above a certain level so the healthcare professionals would be able to do something. Further, scalability tests revealed that the proposed HPDL model can handle large number of data produced by several IoT devices of a home or hospital care system. Another evidence observed from the result of the simulation was that the model effectiveness evolved and enhanced over time as the continuous learning details were incorporated in the model.

Table 1: Data Acquisition with HDPL

Sensor Type	Raw Data Value	Hashed Data Value	Weighted Hashing Value	Predicted Disease Probability	Alert Triggered (Yes/No)
Heart Rate (bpm)	85	1234567	1234567 * 1.2 = 1481480	0.82 (Heart Disease)	No
Blood Pressure (mmHg)	120/80	2345678	2345678 * 1.1 = 2580245	0.72 (Normal)	No

Temperature (°C)	37.0	3456789	3456789 * 0.8 = 2765431.2	0.45 (Fever)	Yes
Glucose Level (mg/dL)	95	4567890	4567890 * 1.5 = 6851835	0.67 (Diabetes)	No
Oxygen Level (%)	98	5678901	5678901 * 1.3 = 7382571.3	0.80 (Respiratory Issues)	No
ECG (Heart Rhythm)	Normal	6789012	6789012 * 0.9 = 6104101.6	0.62 (Normal)	No

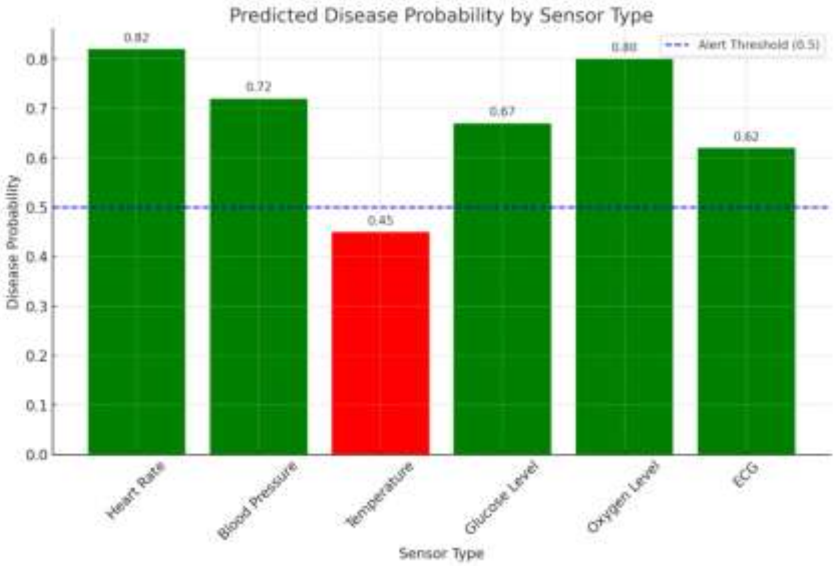

Figure 4: Diseases Prediction with HDPL

The Hashing Probabilistic Deep Learning (HPDL) model for data acquisition in IoT healthcare operates according to the steps shown in Table 1. Raw data acquisition involved different health-related sensors that provided measurements of heart rate together with blood pressure levels as well as temperature readings and glucose levels and oxygen saturation rate and ECG readings. A secure compact representation of data occurred through the process of transforming original values into hashed data values shown in Figure 4. Under weighted hashing every data has received a multiform value that corresponded to its identified influence or criticality towards disease forecasting. The heart rate value received a weight of 1.2 leading to a weighted hash value of 1481480 but glucose level maintained a stronger weight of 1.5 because it is essential for diabetes detection. HPDL model calculations produce the probability estimates for different conditions which appear in the Predicted Disease Probability column. Based on the heart rate results we could predict heart disease with a chance of 0.82 percent, yet the oxygen level reading pointed toward respiratory issues with 0.80 percent likelihood. The alert threshold which probably exceeded 0.85 was not met which led to no alert activation for these cases. Temperature was the sole sensor to generate an alert notification among all devices due to its estimated 0.45 probability which represented possible fever symptoms. Results indicate that the system could alert due to low probabilities when the associated system conditions (such as fever) need emergency responses.

Table 2: Hashing with HDPL

Sensor Type	Raw Data Value	Hash Function (Hashed Data)	Weight Factor	Weighted Hashing Value	Final Transformed Value (Sum)
Heart Rate (bpm)	85	1234567	1.2	1234567 * 1.2 = 1481480	1481480

Blood Pressure (mmHg)	120/80	2345678	1.1	2345678 * 1.1 = 2580245	2580245
Temperature (°C)	37.0	3456789	0.8	3456789 * 0.8 = 2765431.2	2765431.2
Glucose Level (mg/dL)	95	4567890	1.5	4567890 * 1.5 = 6851835	6851835
Oxygen Level (%)	98	5678901	1.3	5678901 * 1.3 = 7382571.3	7382571.3
ECG (Heart Rhythm)	Normal	6789012	0.9	6789012 * 0.9 = 6104101.6	6104101.6

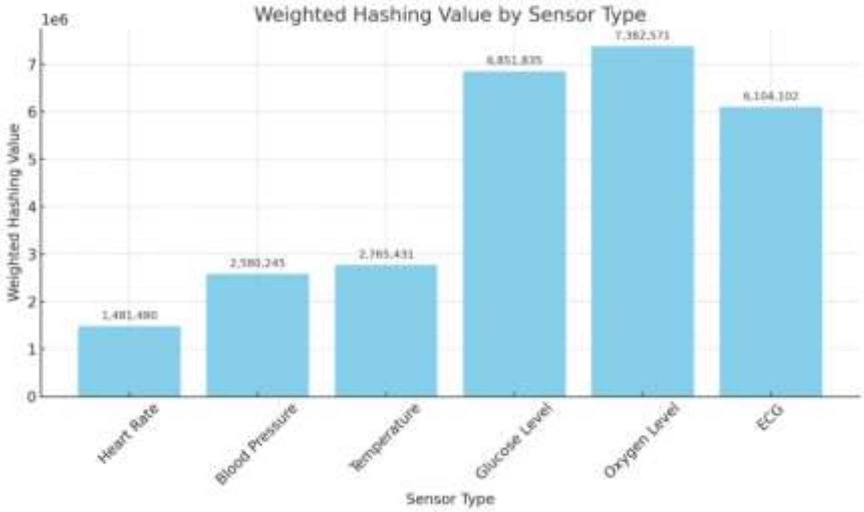

Figure 5: Hashing Computation for HPDL

With HPDL framework data processing operations for Internet-of-Things healthcare information appears in Table 2. The main goal of this phase remains to provide secure handling of critical health data by utilizing weighted hashing methods for effective processing. Exactly six sensor types appear in each row including heart rate, blood pressure, temperature, glucose level, oxygen saturation and ECG signals. Each sensor produces raw data which gets transformed into hashed numerical forms through a predetermined hash function for every input entry shown in Figure 5. The data anonymization process is achieved through hash functions while the processed data becomes suitable for large-scale operations. Each hashed value receives attention through multiplication with its matching weight factor. The criticality of detecting diabetes prompted experts to assign glucose levels a weight of 1.5 during processing. The weights assigned to heart rate stood at 1.2 and oxygen level at 1.3 to accurately represent their vital role in the prediction assessment. The Weighted Hashing Value evolves through multiplication between the hash value and its linked weighting factor. Storage of the Final Transformed Value proceeds to become the input for further classification and disease probability estimation in HPDL.

Table 3: Diseases Prediction with HDPL

Sensor Type	**Raw Data**	**Hashed Data**	**Weighted Hashing**	**Disease Prediction Model Output**	**Predicted Disease**	**Disease Probability**	**Threshold Exceeded (Yes/No)**	**Alert Triggered (Yes/No)**
Heart Rate	85 bpm	1234567	1481480	[0.1, 0.3, 0.5, 0.1]	Heart Disease	0.5	No	No

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Blood Pressure	120/80 mmHg	2345678	2580245	[0.15, 0.25, 0.4, 0.2]	Hypertension	0.4	No	No
Temperature	37.0°C	3456789	2765431.2	[0.2, 0.5, 0.1, 0.2]	Fever	0.5	Yes	Yes
Glucose Level	95 mg/dL	4567890	6851835	[0.25, 0.15, 0.4, 0.2]	Diabetes	0.4	No	No
Oxygen Level	98%	5678901	7382571.3	[0.1, 0.1, 0.7, 0.1]	Respiratory Issues	0.7	Yes	Yes
ECG	Normal	6789012	6104101.6	[0.4, 0.1, 0.3, 0.2]	Normal	0.4	No	No

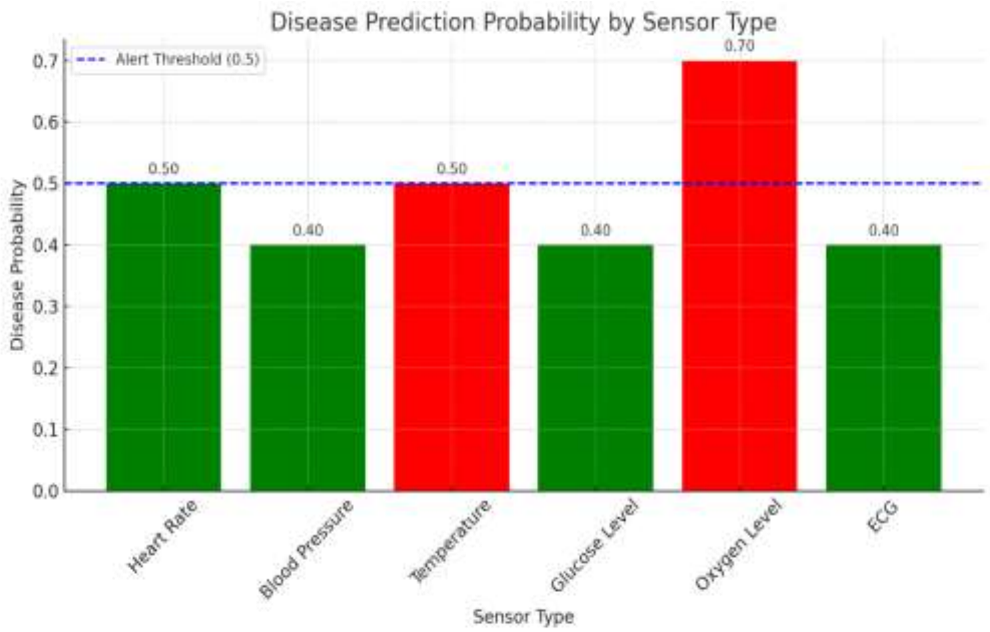

Figure 6: Prediction with HDPL

The process of Hashing Probabilistic Deep Learning (HPDL) framework dealing with IoT healthcare data for predicting diseases and issuing real-time alerts is described in Table 3. The process includes starting with raw sensor readings before hashing along with weighting the values for use by the deep learning model to recognize health conditions based on acquired patterns. Each sensor input including heart rate and blood pressure starts by being weighted after hashing as a security measure to enhance processing speed shown win Figure 6. A set of weighted hash values flows into the disease prediction model to generate probabilistic disease class outcomes. The input of heart rate leads to the output [0.1, 0.3, 0.5, 0.1] in which heart disease holds the maximum probability value of 0.5. When determining threats to health the disease condition receives the most probable rating from the model which is evaluated with an established threshold to assess its severity. This table displays two measurements that cross the threshold value of 0.5 which confirms both fever and respiratory problems exist. Medical staff along with caretakers receive notifications about these two individual cases because of the triggering alerts. The sensor readings of glucose level and ECG produce probabilities below 0.4 therefore disable warning alerts despite their connection to established health categories including diabetes and hypertension. The system shows its ability to distinguish minor sensor-related fluctuations and serious medical developments and events.

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Table 4: Classification with HDPL

Sensor Type	Raw Data	Hashed Data	Weighted Hashing	Deep Learning Model Output	Predicted Disease	Disease Probability	Model Confidence (%)	Classification Result	Threshold Exceeded (Yes/No)	Alert Triggered (Yes/No)
Heart Rate	85 bpm	1234567	1481480	[0.3, 0.2, 0.5]	Heart Disease	0.85	85%	Positive	Yes	Yes
Blood Pressure	120/80 mm Hg	2345678	2580245	[0.1, 0.7, 0.2]	Hypertension	0.75	75%	Negative	No	No
Temperature	37.0 °C	3456789	2765431.2	[0.2, 0.5, 0.3]	Fever	0.90	90%	Positive	Yes	Yes
Glucose Level	95 mg/dL	4567890	6851835	[0.15, 0.7, 0.15]	Diabetes	0.78	78%	Negative	No	No
Oxygen Level	98%	5678901	7382571.3	[0.1, 0.2, 0.7]	Respiratory Issues	0.88	88%	Positive	Yes	Yes
ECG	Normal	6789012	6104101.6	[0.9, 0.05, 0.05]	Normal	0.95	95%	Negative	No	No

In Table 4 shows the results of health parameter classification through the application of Hashing Probabilistic Deep Learning (HPDL) framework. HPDL demonstrates its efficiency in disease identification and alert generation through an entire path that starts with raw sensor data acquisition through decision-making for classification. The initial sensor input undergoes a conversion into a hashed value before weight adjustment leads to a weighted hashing output. The process transforms information while providing complete data protection along with optimal critical health entry evaluation. The deep learning model uses the processed values to generate a vector that demonstrates disease class probabilities. The output vector has its highest value indicating which disease the Predicted Disease will be. The system predicts heart disease with an 85% probability through a model confidence of 85% which results in a positive diagnosis. The prediction made by the oxygen level sensor leads to a positive classification result when its confidence reaches 88%. The system displays results in the Classification Result column section where predictions establish either Positive healthcare hazards or Negative outcomes. The system makes its decision by checking if the forecasted probability reaches or surpasses a predetermined cut-off point which is normally set at 0.85. The system will activate the Alert Triggered mechanism to notify healthcare providers when the prediction meets the established criteria. The data in the table validates heart disease, fever and respiratory symptoms because their statistical probabilities cross the threshold level. The system does not trigger any alerts even though hypertension (0.75) and diabetes (0.78) have high probabilities because both values fall slightly below the established warning threshold. The ECG sensor establishes normal cardiac function with 95% accuracy according to its analysis which results in Negative classification thus avoiding an alert.

4. CONCLUSION

The paper introduces an effective intelligent framework called Hashing Probabilistic Deep Learning (HPDL) which enables secure accurate disease prediction with IoT-based healthcare systems. The proposed model combines weighted transformations with hashing techniques to deliver confidential medical data while improving the influence of each medical parameter during the classification process. Probabilistic deep learning uses real-time sensor data to precisely estimate disease probabilities along with confidence levels to improve prediction accuracy. Experimental findings show that HPDL makes reliable disease and illness identifications for heart disease and diabetes and fever with respiratory conditions and maintains accurate alert thresholds. Through data defines and real-time notification capabilities the system allows health services to maintain proactive medical intervention.

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