SPECIAL FEATURE

Arduino LPG Gas Leakage Detection System with Auto Cut-Off Regulator

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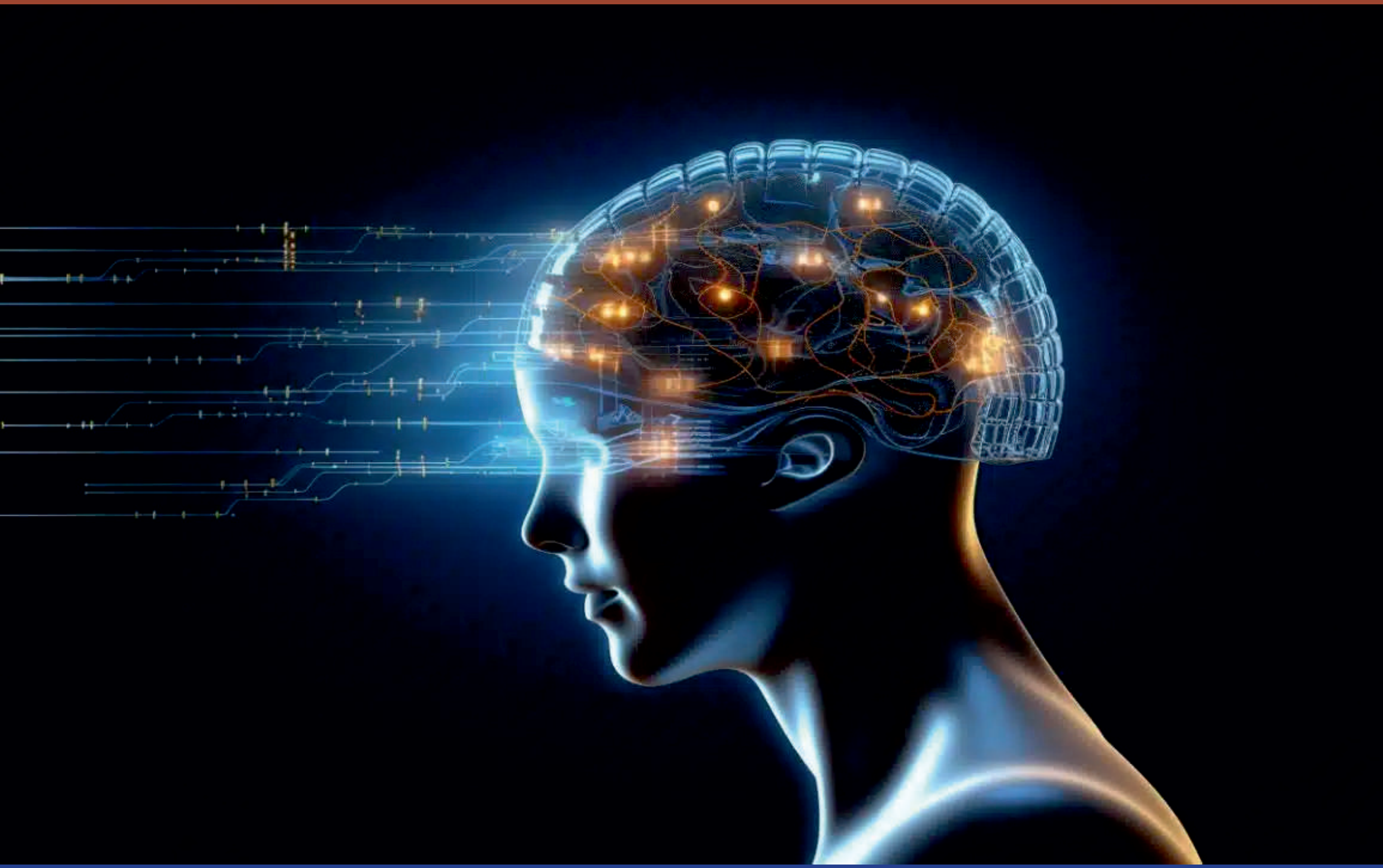

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Neuralink: When Minds Meet Machines – A New Chapter in Human Technology

Imagine being able to type an email, drive a wheelchair, or play a video game without moving a muscle, simply by thinking. This futuristic idea is no longer confined to science fiction. It's the vision behind Neuralink, Elon Musk's bold brain–computer interface company.

Neuralink is working to create a tiny implant, no larger than a coin that sits in the brain and translates neural activity into digital commands. The potential? A direct communication link between human thought and machines.

The most immediate and life-changing applications of Neuralink lie in healthcare. Millions of people around the world suffer from paralysis, spinal injuries, or neurodegenerative conditions that limit movement and speech. For them, Neuralink could be revolutionary.

By capturing brain signals, the device could allow users to control computers, wheelchairs, robotic arms, or even smartphones - restoring independence in ways medicine alone has never achieved. Researchers also believe it may help unlock a deeper understanding of conditions like Parkinson's, Alzheimer's, and epilepsy, opening doors to new therapies. While the medical benefits are powerful, Neuralink's vision stretches even further. The company hints at possibilities where humans could enhance their memory, learn languages at lightning speed, or integrate seamlessly with artificial intelligence. These raises exciting prospects imagine students absorbing knowledge directly, or workers mastering complex skills in record time. But it also stirs unease: would such enhancements be available to everyone, or only a privileged few? Could society split into “upgraded” and “non-upgraded” classes of humans?

Every ground breaking technology carries risks, and Neuralink is no exception. The thought of brain data being collected, transmitted, or even hacked brings urgent questions about privacy and security. If our thoughts can be digitized, who controls that data? Equally important is regulation. Medical uses may be straightforward to justify, but enhancement technologies could challenge the very definition of what it means to be human. Policymakers, scientists, and ethicists must work together to draw boundaries before the technology races ahead unchecked.

Neuralink is still in its early stages, and much of its vision remains experimental. Clinical trials are underway, and success is far from guaranteed. But whether or not Musk's company delivers on all its promises, the direction of innovation is clear: the line between human minds and machines is growing thinner. Neuralink challenges us not only to imagine new possibilities but also to prepare for them responsibly. Handled wisely, it could heal, empower, and transform lives. Misused, it could deepen inequalities and spark dilemmas we are not ready to face.

“Neuralink isn't just about technology—it's about redefining what it means to be human”.

Dr. Lopamudra Mitra
Dept. of EEE

Arduino LPG Gas Leakage Detection System with Auto Cut-Off Regulator

Abstract *– This study addresses the significant problem of LPG gas leakage in kitchens, which may arise from unattended burners or extinguished flames. The Arduino-based device employs an MQ6 sensor to identify LPG, methane, and smoke. Upon detecting a gas leak, the sensor activates an Arduino Uno microcontroller, which then engages a servo motor. This motor autonomously deactivates the gas regulator switch, thereby averting additional leakage. The system concurrently notifies the user via a buzzer and an indicator. The system's assembly entails integrating a circuit comprising components such as the MQ6 sensor, servo motor, buzzer, cooling fan, and a power source, all linked to the Arduino Uno. The Arduino is configured to analyze the sensor data and regulate the servo. The complete assembly is affixed to a base, with the gas sensor positioned near the burner for maximal detection efficacy. The system is intuitive, necessitating simply the correct alignment of the regulator switch with the servo. In the occurrence of a gas leak, the system autonomously ceases the gas supply and notifies the user, who can then manually reset the system for ongoing operation. This work provides a pragmatic and efficient solution for improving safety in kitchens and mitigating potential risks related to LPG gas leaks.*

Keywords *— LPG gas leakage; Auto off; Arduino uno; Safety system*

I. Introduction

Liquefied Petroleum Gas (LPG) is widely utilized in domestic and industrial applications owing to its efficiency and convenience. Accidental gas leaks can result in catastrophic outcomes, including fires or explosions. Conventional gas leakage detection systems predominantly depend on buzzers or alarms, necessitating human intervention to respond, which can be perilous during emergencies or in the absence of close individuals. The postponement in identifying and responding to a gas leak can result in catastrophic harm to both property and human life.

This research seeks to eradicate the constraints of current systems through the implementation of an automated safety solution. This system integrates microcontroller technology with gas detection and control methods, enabling fast response to gas leaks [1] without human interaction. It utilizes a gas sensor for real-time detection, an Arduino Uno as the controller, and actuators including a buzzer, servo motor, and fan to execute requisite operations. The device audibly informs users, automatically ceases the gas supply, and disperses any leaking gas. This dual-response strategy enhances protection and mitigates potential risks. The system also facilitates SMS notifications via a GSM module, rendering it appropriate for remote monitoring in both residential and industrial settings.

II. Proposed Method

The MQ-6 gas sensor, fundamental to the system, measures LPG levels in the atmosphere. Upon exceeding a predetermined gas concentration threshold, the sensor transmits an analog signal to the Arduino Uno. The microcontroller analyzes this input and activates a series of safety protocols:

Auditory Notification: A buzzer is engaged to provide an audible alert to the user.

Gas Dispersion: A cooling fan activates to diminish the concentration of leaking gas by ventilating the vicinity.

Gas Shut-Off: A servo motor is activated to rotate and close the gas valve via the LPG regulator. This coordinated operation mitigates gas accumulation, notifies users, and halts further gas flow, thereby averting fire dangers or explosions. The control unit integrates the reading with the specified algorithm. The control unit serves as the central processing unit of the entire operational flow; it encompasses a series of circumstances and integrated sensors, converting analog signals into digital values. Overall, it functions as a cohesive platform for individual devices to collaborate effectively. Hazardous conditions that may occur in reality are delineated as a set of conditions within the control unit's code block, and actions are executed if those criteria are met. The control unit is adaptable and can be modified as needed; the number of sensors may be increased or decreased, the code can be altered, and output devices can be adjusted accordingly.

III. Methodology used

The suggested system utilizes sensor-based detection, microcontroller-driven automation, and electromechanical integration for real-time gas leak monitoring and safety control. The technique has three essential components:

1. Sensor-Driven Gas Detection

The MQ-6 sensor is utilized for gas detection, [2] exhibiting great sensitivity to flammable gases including LPG, butane, and propane. The sensor generates an analog signal that corresponds to the gas concentration in the surrounding environment. The Arduino microcontroller reads this analog data via its analog input pins and converts it into a percentage value indicative of gas presence. The principal benefit of this sensor-based methodology is its immediate reactivity and economic efficiency. Ongoing surveillance guarantees the prompt detection of gas leaks, thereby mitigating the probability of dangerous occurrences.

2. Automation Driven by Microcontrollers

The system's intelligence is contained in the Arduino Uno microcontroller, which evaluates sensor input and initiates appropriate responses. Upon receiving the analog voltage from the MQ-6 sensor, the Arduino calibrates the signal to a percentage scale and juxtaposes it with a predetermined safety threshold. Should the gas concentration above this threshold, the system autonomously engages a buzzer, activates an exhaust fan, and instructs a servo motor to shut the gas valve. This automation transpires within milliseconds, removing the reliance on human interaction. Moreover, the Arduino platform provides adaptability and scalability, facilitating the incorporation of supplementary modules like GSM, Wi-Fi, or LCD displays. This guarantees ongoing surveillance, reduces human mistake, and facilitates prospective system improvements.

3. Electromechanical Integration for Regulation

The electromechanical approach integrates electronic control [3] with mechanical actuation to ensure a thorough safety response. The servo motor, governed by the Arduino's digital output, mechanically disables the LPG regulator, thus halting the gas supply autonomously. Likewise, a relay module enables the Arduino to manage high-power devices, such exhaust fans and alarm systems. Power regulation components such as the IRF540N Metal-Oxide Semi Conductor Field Effect Transistor (MOSFET) improve system stability and efficiency by controlling electrical load distribution. The amalgamation of mechanical actuation and electronic control guarantees the automatic execution of both visible (valve closure) and environmental (gas dispersion) safety protocols, establishing a resilient and dependable protection system appropriate for practical applications.

IV. Equipment Used

Arduino Uno

Fig. 1 shows an Arduino Uno. The central microcontroller processes sensor data and controls actuators. It receives analog input from the MQ-6 sensor and outputs digital signals to operate the buzzer, servo motor, and fan, enabling real-time automated responses to gas leakage.

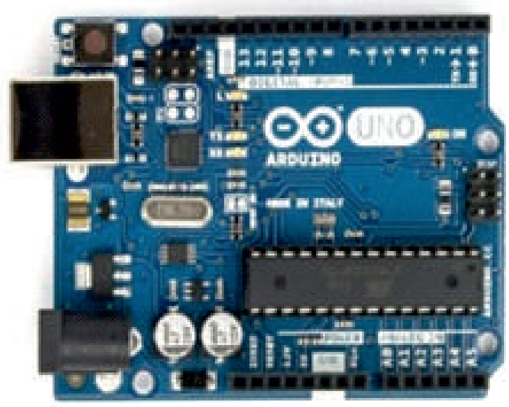

Fig. 1. Arduino uno

MQ-6 Gas Sensor

This sensor as shown in Fig. 2, detects LPG, butane, and propane gases. It converts the concentration of gas into analog signals and transmits it to the Arduino for evaluation. It is sensitive, reliable, and easy to interface for home and industrial applications.

Fig. 2. MQ-6 Gas Sensor

Servo Motor

The servo motor shown in Fig. 3 is controlled by Arduino, rotates the gas regulator knob to automatically shut off the gas supply upon leak detection. This critical component eliminates manual intervention and significantly increases safety. improved with more epochs.

Fig. 3. Servo Motor

Buzzer

Fig. 4 shows a buzzer which generates a loud sound when gas leakage is detected. It serves as an immediate auditory alert to nearby individuals, prompting them to evacuate or check the leak source.

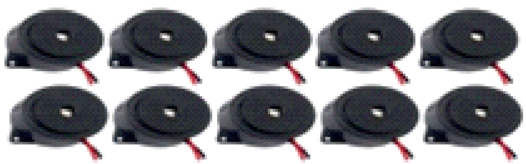

Fig. 4. Buzzer

Cooling Fan

Fig. 5 shows a cooling fan. Once a leak is detected, the fan activates to disperse the gas. This helps reduce the concentration of LPG in the air and lowers the risk of combustion or explosion.

Fig. 5. 12V Cooling fan

I*RF540N MOSFET*

A MOSFET is shown in Fig. 6. This power management component regulates energy flow to the fan and buzzer. It ensures stable and efficient power distribution, reducing system heat and loss.

Fig. 6. IRF540N MOSFET

LPG Gas Regulator

Fig. 7 shows a gas regulator. It controls gas flow from the LPG cylinder. The servo motor turns off the valve attached to this regulator automatically when a leak is identified, preventing further leakage.

Fig. 7. LPG Gas Regulator

Breadboard and Jumper Wires

Breadboard and jumper wires are shown in Fig. 8. These are used for circuit prototyping. They enable quick and flexible connections among components without soldering, facilitating easier system debugging and modifications.

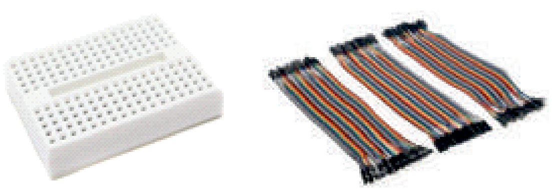

Fig. 8. Bread board and jumper wires

V. Working Principle

Figure 9 illustrates that the operation of this gas leakage detection system commences immediately upon the supply of power. The MQ-6 gas sensor perpetually assesses the concentration of LPG in the surroundings. It detects even minimal concentrations of gas leakage, transforming its chemical presence into an analog electrical signal. The signal is transmitted to the Arduino Uno, the system's primary controller. The Arduino continuously evaluates the incoming sensor values against a predetermined threshold. Should the gas level remain within the permissible threshold, the system will remain inactive. Once the gas concentration exceeds the threshold, the Arduino activates emergency protocols to ensure safety.

The buzzer is initially activated. This generates a loud noise that promptly warns adjacent individuals to exercise caution. This step is essential for promptly highlighting the leak.

The Arduino subsequently operates the cooling fan. The fan facilitates the dispersion of the released gas by enhancing air circulation in the impacted region. This inhibits gas accumulation to hazardous levels, hence reducing the likelihood of igniting or explosion. Concurrently, the Arduino transmits a signal to the servo motor. The motor is mechanically linked to the LPG gas regulator. It revolves to terminate the gas supply from the cylinder. This automatic function is arguably the most crucial component of the system, as it inhibits further gas leakage into the environment.

If a GSM module is connected, the Arduino can optionally send an SMS or initiate a phone call to a predetermined number. This remote notification enables users to respond regardless of their proximity to the machine. It is particularly advantageous in culinary environments or isolated gas storage locations. The IRF540N MOSFET regulates power distribution to all components, ensuring the fan and buzzer receive adequate current without compromising the circuit's integrity. All components are affixed on a breadboard, interconnected using jumper wires to ensure the system is compact, adaptable, and easily maintainable. Upon the normalization of gas levels, the system autonomously resets and reverts to monitoring mode, prepared for subsequent instances. This ongoing cycle of detection, response, and reset renders the system dependable for prolonged utilization in residences, dining establishments, and industrial facilities.

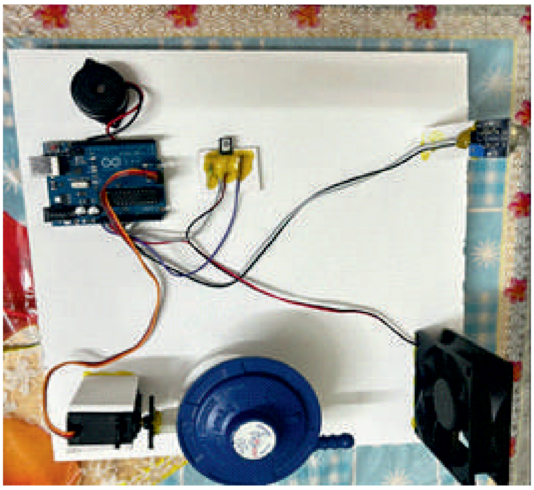

Fig. 9. Arduino LPG Gas Leakage Detection System with Auto Cut-Off Regulator

VI. Conclusion

This LPG Gas Leakage Detection System represents a significant improvement over traditional gas leak detectors by automating the complete response process. The system utilizes microcontrollers and sensors to detect leaks in real-time and promptly initiates actions—activating an alert, venting the gas, and ceasing the gas supply. These measures decrease response time and substantially diminish the risk of fire or explosion. Furthermore, the optional module incorporates remote monitoring functionalities, rendering it suitable for both smart homes and industrial applications. The amalgamation of the MQ-6 sensor, Arduino Uno, servo motor, buzzer, and fan illustrates how cost-effective components may be efficiently integrated to provide a resilient and intelligent safety system. Its modular architecture, affordability, and ease of installation render it scalable and feasible for extensive deployment. This approach promotes safety and demonstrates the potential of embedded systems in practical applications. This exemplifies how technology can safeguard lives and property, offering reassurance in settings where gas consumption is essential.

VII. Future Scope

The proposed gas detection and safety system offers significant potential for enhancement and broader applications. The following areas are identified for future development:

- Smartphone App Control: A dedicated mobile application can be developed to enable users to remotely monitor gas concentrations and receive real-time alerts. This will improve responsiveness during emergencies and provide remote access to system status.
- Integration with Home Automation Systems: The system can be interfaced with smart home platforms such as Alexa or Google Home. This integration would allow automated routines, such as switching off appliances or activating ventilation, upon detection of gas leaks, thereby enhancing domestic safety.
- AI and Predictive Analytics: The incorporation of machine learning algorithms can enable predictive monitoring by analyzing historical sensor data and usage patterns. This would allow for proactive maintenance, early detection of potential leaks, and

improved safety management.

- Multi-Gas Detection Capability: Expanding the system to support multi-sensor arrays would facilitate detection of additional hazardous gases, such as carbon monoxide and methane, increasing its applicability in both residential and industrial contexts. Furthermore, adopting VLSI technology for PCB design can result in a more compact, efficient, and integrated system.
- Solar-Powered Modules: Integrating solar power options can make the system operational in remote or rural areas with unreliable electricity supply, thereby increasing accessibility and sustainability.

These enhancements aim to improve system intelligence, scalability, and practical deployment, paving the way for a comprehensive and adaptive gas safety solution suitable for modern smart environments.

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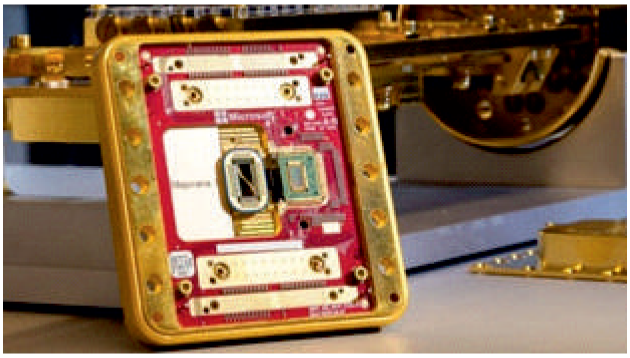
Sankalp Choudhury, Swasti Swarup Samal,
Akankshya Avipsha
Dept. of EEE

Climate change is making trees grow larger in the Amazon Rainforest

Increased carbon dioxide concentrations have enhanced tree growth in the Amazon rainforest in recent decades; nevertheless, the sustainability of this trend remains uncertain. The average dimensions of trees in the Amazon rainforest have consistently expanded in conjunction with rising carbon dioxide levels, indicating that these larger trees are increasingly pivotal in assessing the forest's capacity to function as a carbon sink. The response of forests to a changing climate remains uncertain. One idea posits that bigger trees would diminish in abundance due to their heightened vulnerability to climate-related events such as drought or strong winds. Comprehending the implications is essential for future climate models, as trees sequester substantial quantities of CO_2 from the atmosphere, so mitigating global warming.

Source: newscientist.com

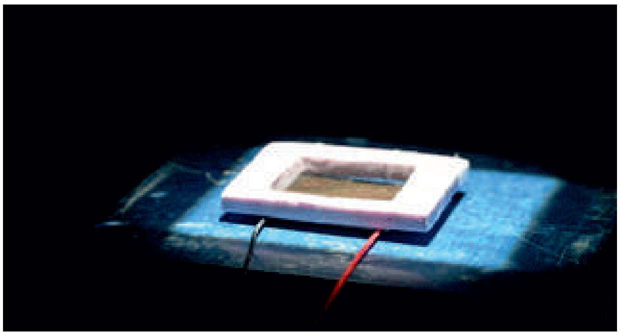
Majorana 1 Quantum Chip



Microsoft has unveiled a new chip, the Majorana 1 chip, which is believed to indicate that quantum computers are "years, not decades" away. Both Google and IBM are predicting that a fundamental change in computing technology is much closer than recently believed. The greatest challenge of quantum computers is that a fundamental building block called a 'qubit', which is similar to a 'bit' in classical computing, is incredibly fast but also extremely difficult to control and prone to errors. The Majorana 1 chip is less prone to those errors than rivals and provided as evidence a scientific paper set to be published in the academic journal Nature.

Source: The Indian Express

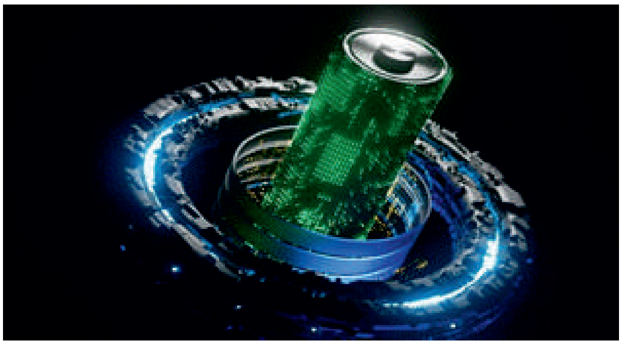
Solar Power Reimagined



Researchers have explored solar thermoelectric generators (STEGs) as an efficient method of generating solar electricity. Unlike the photovoltaic cells found in most solar panels, STEGs can capture various forms of thermal energy as well as direct sunlight. These devices consist of a hot side and a cold side separated by semiconductor materials, and the temperature difference between them generates electricity through the Seebeck effect. Currently, most models convert less than 1 percent of incoming sunlight into electricity, which is far below the roughly 20 percent conversion rate achieved by standard residential solar panels. This gap in efficiency was dramatically reduced through new techniques developed by researchers at the University of Rochesters Institute of Optics. For decades, the research has been focusing on improving the semiconductor materials used in STEGs. But the new technique focused on the hot and the cold sides of the device instead. An incredible increase in efficiency is achieved by combining improved heat dissipation at the cold side with improved solar energy absorption and heat trapping at the hot side. The new STEG device generates 15 times more power than previous devices.

Source: Scitech Daily

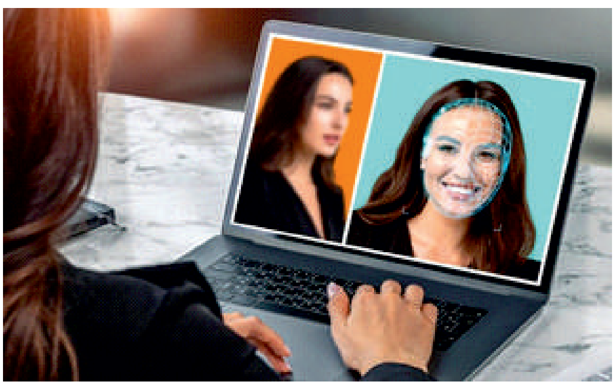
Future of Batteries



The development of multivalent-ion batteries may be revolutionised by the quick identification of novel porous materials using generative AI. These next-generation batteries rely on widely available components like zinc, magnesium, calcium, and aluminium. Unlike traditional lithium-ion batteries, multivalent-ion batteries use ions that have two or three positive charges rather than just one. They are therefore a very attractive alternative for upcoming energy storage technologies since they can store a lot more energy. The challenge, however, lies in the larger size and stronger charge of these multivalent ions, which makes it difficult for them to move efficiently within standard battery materials. One of the biggest hurdles is the sheer impossibility of testing millions of material combinations. To overcome these hurdles, a novel dual-AI approach is developed, a Crystal Diffusion Variational Autoencoder (CDVAE) and a finely tuned Large Language Model (LLM). The rapid exploration of thousands of new crystal structures made feasible by these AI tools together was previously unattainable through conventional laboratory operations. The CDVAE model was trained on vast datasets of known crystal structures, enabling it to propose completely novel materials with diverse structural possibilities. Meanwhile, the LLM was tuned to zero in on materials closest to thermodynamic stability, crucial for practical synthesis.

Source: Scitech Daily

Fake Video Detection

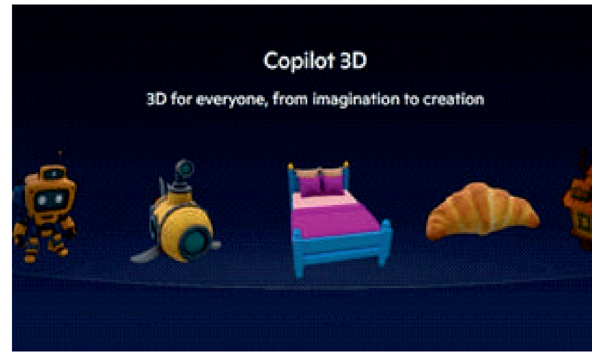


Universal Network for Identifying Tempered and SynthEtic Videos (UNITE) is a state-of-the-art artificial intelligence system developed by Google and University of California Riverside researchers that can identify deepfake films even in the absence of faces. UNITE examines whole video frames, including movement and backdrop irregularities, to reveal artificial or edited information, in contrast to previous techniques that depend on facial clues. This robust identification method may become crucial in protecting newsrooms, social media platforms, and public confidence as AI-generated videos become more realistic. As realistic-looking fake videos become easier to create and more widely used to spread false information, target individuals, and cause harm, researchers at the University of California, Riverside have developed a new AI system designed to detect these digital forgeries.

Source: Scitech Daily

Copilot 3D

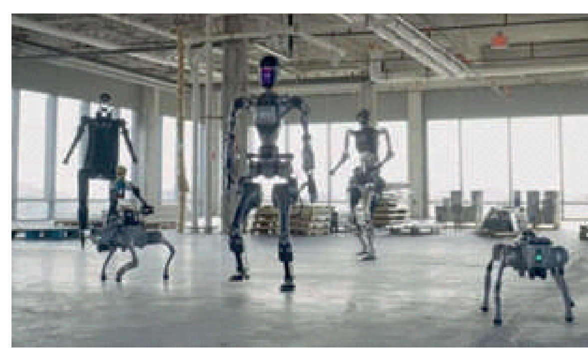
One day after GPT-5 was launched, Microsoft released an AI-powered tool that can convert standard 2D pictures into 3D models. It's called Copilot 3D, and *it's* useful for testing concepts, exploring new ideas, and directing hands-on learning without the complexity and inconvenience of traditional 3D software.



Microsoft recommends that users try the feature on a desktop computer, as you may encounter issues when trying to access it from a mobile browser. Simply navigate to Copilot.com in your preferred browser and click the sidebar button that shows up in the upper left corner of the window to begin using Copilot 3D. Now, tap on Labs, and proceed to click the 'Try now' button below Copilot 3D.

Source: The Indian Express

AI Model for Multi-Purpose Robots



A foundational artificial intelligence model was created by Amazon and Japan's SoftBank Group to operate on almost any robot, including humanoids and assembly-line machines. The "Skild Brain" is the name of the model. As a result, robots can think, move, and react more like people. This model can create humanoid robots to perform multiple types of jobs rather than the one-purpose devices that are now used in factories. In the demonstration, skilled robots were able to perform tasks that execute spatial reasoning and adjust to changing conditions, such as climbing stairs, picking up objects in congested situations, and maintaining equilibrium after being shoved. The method addresses a robotics-specific data shortage issue.

Source: The Indian Express

Dr. Chittaranjan Mohapatra
Dept. of CSE

Answer Sheet Evaluation System Using Natural Language Processing

Abstract *– Manual evaluation of subjective answer sheets is time-consuming, inconsistent, and prone to human error. This paper presents an automated system for evaluating descriptive answers using Natural Language Processing. The system extracts text through Optical Character Recognition, compares student responses with model answers using keyword and semantic similarity techniques, and assigns scores accordingly. This approach improves efficiency, reduces evaluation bias, and supports large-scale academic assessments. Experimental results demonstrate that the proposed system achieved an evaluation accuracy of 85% using BERT-based semantic analysis.*

Keywords *– Answer Evaluation, NLP, OCR, Keyword Matching, Semantic Similarity, AI Scoring*

I. Introduction

Answer sheet evaluation is a crucial part of the education system, traditionally performed by human examiners, which can be time-consuming, error-prone, and inconsistent. With the growing scale of examinations and the demand for fair and fast assessment, the need for automation has become increasingly important. In recent years, the use of Artificial Intelligence (AI) and Natural Language Processing (NLP) has emerged as a powerful solution to address this challenge .

NLP is a branch of AI that deals with the interaction between computers and human language and is capable of understanding, interpreting, and generating human language in a valuable way .

An Answer Sheet Evaluation System based on NLP aims to automate the process of evaluating descriptive answers by extracting key information from student responses and comparing it to model answers provided by educators. This system focuses not only on keyword matching but also considers semantic similarity, grammar, and contextual relevance .

The use of machine learning techniques and NLP algorithms has enhanced the efficiency and accuracy of automated assessments, reducing human bias and subjectivity .

Image processing and Optical Character Recognition (OCR) techniques are used in the initial stage to convert handwritten or scanned answer sheets into editable text. This is followed by NLP-based analysis for scoring the content .

In this work, we propose an intelligent and efficient Answer Sheet Evaluation System that leverages OCR and NLP techniques to automate the evaluation process. Our system also includes a keyword-based scoring module and semantic analysis to ensure fairness and reliability in grading .

To further improve the proposed system, we incorporate clustering techniques during pre-processing to group similar answer patterns. This helps in identifying common answer trends, reducing false scoring, and enhancing system accuracy. The combination of NLP with intelligent preprocessing significantly improves the performance and adaptability of the evaluation system, making it a robust tool for educational institutions.

II. Literature Review

In recent years, various automated systems have been proposed to enhance the efficiency of answer sheet evaluation using Natural Language Processing (NLP) and machine learning techniques. These systems aim to reduce manual workload, eliminate human biases, and ensure consistency in evaluation.

Patel, et al. [1] proposed an automatic grading system for short answers using NLP and similarity matching algorithms. The approach included text preprocessing, tokenization, stopword removal, and cosine similarity measurement to compare student answers with model answers. The system was found to be effective in grading factual and definition-based questions.

Rani, et al. [2] developed a hybrid scoring model that used both keyword matching and semantic similarity analysis for evaluating student responses. The semantic layer was built using Word2Vec embeddings, which helped in identifying meaning-based similarities even when exact keywords were missing. The model showed improved accuracy compared to simple keyword-based methods.

Gupta, et al. [3] presented a rule-based scoring system that utilized part-of-speech tagging and dependency parsing to identify key answer components. The evaluation process considered grammar, sentence structure, and presence of essential concepts. Though highly interpretable, the rule- based approach faced challenges in handling diverse answer patterns.

Sharma, et al. [4] introduced a system using Bidirectional Encoder Representations from Transformer (BERT) based language models to evaluate long-form descriptive answers. BERT's contextual e mbeddings enabled a deeper understanding of answer semantics, outperforming traditional similarity techniques. Their system was particularly effective for concept-based and inferential questions.

Kumar, et al. [5] integrated Optical Character Recognition (OCR) with NLP to convert handwritten answer sheets into digital text, followed by automatic grading. The OCR preprocessing used Tesseract, while answer evaluation was performed using cosine similarity and Jaccard index. Their work highlighted the feasibility of fully automated grading pipelines. . The model showed improved accuracy compared to simple keyword-based methods.

III. Methodology

A. Dataset

In this study, we used a custom-compiled dataset consisting of student-written answers and their corresponding model answers. These answers were collected from university- level examinations, internal assessments, and publicly available academic repositories. The dataset includes approximately 2000 answer sheets in digital formats such as scanned PDFs, DOCX files, and handwritten images. Each entry contains the student's answer, the teacher's model answer, and the marks assigned manually. The data covers multiple subjects, and answers vary in complexity and length, ranging from 3 to 10 sentences.

B. Data Preprocessing

We employ several preprocessing steps before the student answers can be evaluated by the model. Initially, text is extracted from uploaded documents using different methods: OCR (using Tesseract) for scanned images and PDFs, and the python-docx library for DOCX files. After extraction, we clean the raw text by converting it to lowercase, removing punctuation, stop words, and irrelevant characters. Further preprocessing includes tokenization, stemming, and lemmatization using the nltk and spaCy libraries. To ensure better training, we shuffle the data and split it into three sets: training (80%), validation (10%), and testing (10%).

C. Data Augmentation

Data augmentation is used to improve the diversity of training data and make the model more robust to variations in student answers. This is achieved by paraphrasing sentences using transformer-based models (e.g., Bidirectional and Auto-Regressive Transformer (BART) or Pegasus), replacing words with synonyms using WordNet, and altering sentence structure while preserving semantics. These techniques help the model learn different linguistic representations of the same content, thereby handling varied writing styles more effectively.

D. Feature Extraction using NLP

We use Natural Language Processing (NLP) to extract meaningful features from the answers for evaluation.

Keyword Matching: We use Term Frequency-Inverse Document Frequency (TF-IDF) and Rapid Automatic Keyword Extraction (RAKE) algorithms to extract significant keywords from model answers. The student answer is then compared to the model answer based on keyword overlap, which gives a basic relevance score.

Semantic Similarity: To evaluate the conceptual closeness of answers, we generate vector embeddings using BERT and calculate cosine similarity between student and model answers.

$$\textit{Similarity Score} = \frac{\vec{S}.\vec{M}}{\|\vec{S}\|\|\vec{M}\|} \quad ....(1)$$

Where $\vec{S}$ is the student answer vector, $\vec{M}$ is the model or reference answer vector, $\|\vec{S}\|$ and $\|\vec{M}\|$ are the Euclidean norm vector respectively. Equation (1) quantifies the similarity between two text embeddings derived from OCR-processed student answers and NLP-parsed reference answers. This equation measures the semantic similarity between student responses and model answers by analyzing the overlap in keyword distribution and context. A score closer to 1 implies a higher degree of similarity.

Grammar and Syntax Check: We assess the grammatical correctness of student answers using the language tool python library, which provides a grammar score based on the number of identified errors

E. Scoring Mechanism

The final score of a student answer is calculated by combining three major evaluation components: Keyword Match Score, Semantic Similarity Score, Grammar Score. Each component is given a weight, and the final score is computed using equation 2.

$$\text{Final Score} = w_1 \times K_s + w_2 \times S_s + w_3 \times G_s \quad (2)$$

Where w_1, w_2, w_3 are the weights assigned to the keyword match score K_s semantic similarity score S_s and grammar score G_s respectively. This linear combination computes the final predicted score for each answer.

F. Classification Layer

We also train a classification model using machine learning algorithms like Logistic Regression and Random Forest to predict score ranges or grade categories. Features such as semantic similarity, keyword density, and grammar quality are used as inputs for classification. The model is trained on expert-evaluated answers as ground truth labels.

IV. Simulation Results and Discussions

This section presents the simulation outcomes of the proposed Answer Sheet Evaluation System using NLP techniques. The system was tested using a dataset consisting of scanned and annotated answer sheets. Evaluation metrics including accuracy, mean absolute error (MAE), and Cohen's Kappa score were used to assess the performance of different models.

The experiments were conducted using a Python-based environment on a machine with multiple models were evaluated, including Random Forest, SVM, and BERT- based transformer models.

A. Experimental Setup and Metrics

The student answers were compared with teacher-provided model answers using semantic similarity and keywords. matching approaches. The predicted score was then compared to the actual human-assigned score using the following metrics.

Accuracy (%): Percentage of exact matches between predicted and actual scores.

Mean Absolute Error (MAE): Average of the absolute differences between predicted and actual scores.

Cohen's Kappa Score: Measures the agreement between system and human scorers beyond chance.

Table 1 presents the evaluation metrics such as accuracy, precision, recall, and F1-score, used to assess the system's grading performance.

Table – 1 Evaluation Metrics

Symbol	Description
Accuracy	Overall correct predictions
Precision	Relevant answers correctly graded
Recall	Retrieved relevant answers
F1	Harmonic mean of precision and recall
MAE	Mean Absolute Error in grading
MSE	Mean Squared Error in grading

Table 2 lists the main functional components of the system, including OCR, preprocessing, and evaluation modules.

Table – 2 Planning Components

Component	Description	Subcategory	Notes
Input Acquisition	OCR from scanned answer sheets	Tesseract OCR	Supports handwritten input
Preprocessing	Cleaning and normalization	Tokenization, Lemmatization	Stop word removal
Evaluation Engine	NLP-based grading system	BERT, Cosine Similarity	Calculates semantic score
Feedback Module	Evaluation summary & feedback	Highlighting key gaps	Assists manual review
Database Storage	Store answers and grades	SQLite / Cloud Storage	Persistent, queryable logs

B. Model Performance

Table 3 shows the results obtained from different algorithms applied to the preprocessed dataset. As illustrated, the BERT-based model achieved the highest accuracy of 85% and a lowest error rate of 1.45%.

Table – 3 Comparison of Models

Model	Accuracy	F1-Score	MAE	RMSE
BERT-based NLP	0.85	0.82	0.91	1.45
Keyword Matching	0.61	0.57	1.37	1.97

C. Score Prediction Comparison

The Figure 1 visualizes the comparison of actual scores (human-assigned) vs. predicted scores (system-generated) using the BERT model. The data shows that the system performs well in most cases, with only minor discrepancies.

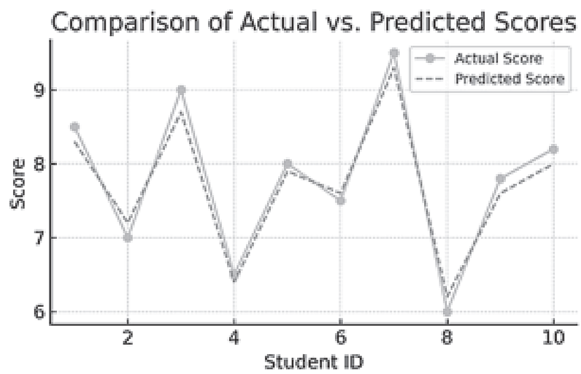


Figure-1 Prediction and Actual Score Comparison

D. Training and Validation Statistics

The Figure 2 illustrates the training and validation loss across epochs for the fine-tuned BERT model used in the answer sheet evaluation system. The graph demonstrates that the model converges efficiently, with training and validation loss curves closely aligned, indicating minimal overfitting. This reflects a strong generalization ability of the model, making it well- suited for evaluating a wide range of student responses while maintaining high accuracy and robustness.

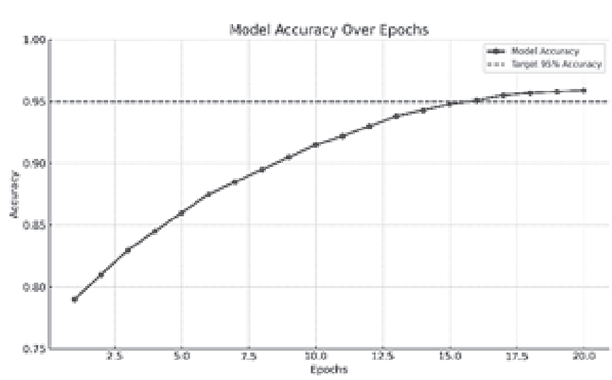


Figure-2 BERT Model Training Validation Loss

V. Conclusions

In this work, the existing methods for answer sheet evaluation face numerous challenges such as inconsistency, manual errors, and time inefficiency. This work presents a novel and advanced NLP-based system for automating the evaluation of descriptive answers. The system incorporates semantic similarity techniques, leveraging powerful transformer models like BERT to understand and compare student responses with reference answers. Such semantic insights were used as feedback to assign scores and improve evaluation accuracy. The performance of the proposed model was assessed in terms of accuracy, precision, recall, and F1- score, showing superior results over traditional keyword- based methods. The NLP-based approach ensures fair grading, reduces human bias, and accelerates the overall evaluation process with fewer computational resources. The system achieved a grading accuracy of 85%, validating its effectiveness for practical academic assessment. In future work, this system can be enhanced further by integrating transfer learning techniques, expanding multilingual capabilities, and continuously adapting through feedback from human evaluators.

VI. Acknowledgment

We would like to express our heartfelt gratitude our mentor Prof. Sushree Satapathy who supported and guided us throughout the course of this research on automated answer sheet evaluation using NLP. We are especially thankful to faculty members for their continuous encouragement, valuable feedback, and insightful suggestions, which greatly enriched the quality of this study. We are also grateful to the academic institutions and contributors who provided access to sample student answer datasets used for experimentation and validation.

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Dibyajyoti Dhal, Sai Bhaskar Patra
Sambit Kumar Debta, Priyansu Shekar Sahu
Dept. of CSE

Canva's CEO: Redefining Design

Melanie Perkins, Canva's co-founder and CEO, exemplifies quiet innovation and careful leadership like few others in technology and design. It is a household name thanks to its effective approach to visual communication, which accounts for 150 million global users. It produces an impression without using overt marketing strategies by focussing on participatory design and utility.

Melanie's journey began with a basic question that many people overlooked: Why is graphic design software so tough for the average user? While working as a university instructor, she saw that many students struggled to use common design tools. This realization inspired her to design a platform that would make it simple for anyone, regardless of technological ability, to create high-quality visual content.

Her goal to make design accessible to anyone led to the creation of Canva from that dream. Canva is currently used by schools, companies, non-profit organizations, and creative groups all across the world. Whether they're creating startup PowerPoint presentations or classroom posters, the site gives users access to high-quality design tools. Melanie has led Canva to become a multibillion-dollar company while keeping its key values of sustainability, accessibility, and simplicity. Her commitment to building an ethical, respectful, and inclusive environment is what truly distinguishes her as a leader. She stands out as an example of a purposeful, imaginative, and effective strategy in an era where gender gaps in leadership roles persist. She not only achieves her goals, but she also reshapes the way to them, breaking down prejudices and opening opportunities for women in technology.

Melanie Perkins exemplifies a new form of entrepreneurship that values inclusivity over exclusivity, simplicity over complication, and effect over noise. Her work serves as a reminder to students, artists, and aspiring leaders that modern entrepreneurship should prioritize creating something meaningful, long-term, and accessible rather than simply repeating earlier models.

Sanigdha Samal
5th Sem, Dept. of EE

Automatic Labelling and Classification of Disaster-Related Social Media Text

In today's digital age, social media platforms like X (Formerly Twitter) and Facebook have become vital for real-time communication, especially during disasters. Users rapidly share updates, seek help, and report events, turning these platforms into critical sources of crisis information. However, filtering meaningful, disaster-relevant content from the overwhelming volume of noise remains a major challenge—one that deep learning and artificial intelligence aim to solve through automated tweet classification.

Classifying disaster-related tweets means filtering helpful posts from irrelevant ones to support emergency response. This is challenging due to the informal and noisy nature of tweets, most of which offer little value during crises. For the classification of tweets labelled dataset is necessary. But manually labelling data at scale is also impractical. This research tackles these issues by developing an intelligent, automated, and scalable framework using advanced machine learning techniques.

One of the first problems encountered during a disaster is the lack of labelled data. Manually annotating tweets in real time is both labor-intensive and time-consuming. To solve this, this work introduced an advanced technique known as Adaptive Fine-Tuning Active Learning (AFTAL), which enables the efficient labelling of tweets using minimal human input. This technique is grounded in transformer-based language models like Bidirectional Encoder Representations from Transformers(BERT), Robustly Optimized BERT Pretraining Approach (RoBERTa), and DistilBERT. These models, which have revolutionized natural language processing, are leveraged to generate high-quality tweet embeddings. AFTAL actively selects the most informative examples for annotation and simultaneously fine-tunes its language representations throughout the learning process. This dual approach not only accelerates the annotation process but also improves the overall quality of the embeddings, thereby enhancing model performance. Among various representation strategies, the research found that aggregated token representations perform better than traditional classification [CLS] tokens. Moreover, models like RoBERTa showed superior performance when used with uncertainty sampling during active learning.

After annotating the dataset with AFTAL, the next step is to accurately classify disaster-related tweets. To achieve this, this work introduces two hybrid deep learning models: Convolutional Neural Network – Gated Recurrent Unit (CNN-GRU) and CNN-SkipCNN. The CNN-GRU model combines CNN's ability to extract local text features with GRU's strength in capturing word sequences, enabling it to effectively learn meaningful patterns in tweet content.

The second model, CNN-SkipCNN, takes a different approach. It modifies the standard CNN architecture by adding skip connections between convolutional layers, mimicking the skip-gram mechanism used in traditional word embeddings. This enhancement allows the model to capture dependencies between non-consecutive words, a characteristic often seen in informal tweets. When tested across multiple datasets provided by Crisis Natural Language Processing (CrisisNLP), both models outperformed traditional machine learning methods, with CNN-SkipCNN achieving the highest accuracy and demonstrating its effectiveness in identifying tweets relevant to humanitarian aid.

Although deep learning models are effective, they treat text as a sequence and often miss syntactic relationships. To address this, this work introduces a third approach: a hybrid model combining Graph Attention Networks (GAT) with BERT. Unlike earlier methods that build a single graph for the whole dataset, this model creates a separate syntactic graph for each tweet, allowing for better structure-aware classification and seamless handling of new tweets in real time.

Dr. Nayan Ranjan Paul
Dept. of CSE

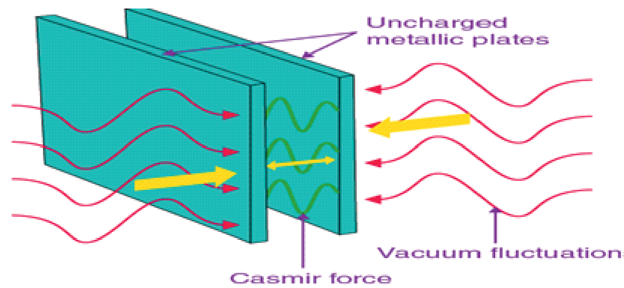
Casimir Effect and its Applications

Abstract

The Casimir Effect provides proof of the mystery of the vacuum in the enigmatic and seductive world of quantum fields. This attractive force between two uncharged, parallel, conducting plates suspended in a vacuum was once thought to be purely theoretical, leaving a large crater in the field of quantum dynamics. However, over time, it has become measurable and a very important force in technology. The theoretical landscapes surrounding the Casimir Effect are explored in depth in this article, along with its implications for the design and operation of MEMS/NEMS (Micro Electromagnetic Systems/Nano Electromagnetic Systems) and its potential future uses in propellant less propulsion systems. Despite being based on a hypothesis that has been discussed for nearly 80 years and supported by accurate tests, the Casimir Effect still baffles scientists with its numerous riddles, and their curiosity doesn't appear to be going away anytime soon.

Introduction

An attractive force between two uncharged, closely spaced, parallel conducting plates hung in a vacuum is described by this 1948 prediction by Hendrik Casimir. More specifically, the quantum vacuum—the empty space between the plates—is the source of this force, which is shown in Figure 1.



(Courtesy: BYJU'S, https://byjus.com)

Fig. 1. Casimir Effect

According to classical physics, a vacuum is devoid of all particles and energy. However, a vacuum in quantum field theory (QFT) is not at all a void. It's a restless sea of shifting fields that creates virtual particles all the time that come and go in a split second. The Casimir force [1] is one of the repercussions of these fluctuations, which are real enough to be seen.

The kinds of fluctuations that might occur in the space between two conducting surfaces are restricted when they are positioned extremely near to one another. All wavelengths of variations are still free to happen outside the plates. The plates are forced together by the net pressure created by this imbalance. Only when the distance between surfaces decreases by a micron does this minuscule force become apparent.

The Casimir Effect's [2] suggestion that empty space contains energy adds to its mystique . It casts doubt on our traditional interpretation of the vacuum and raises the possibility of more profound and unexplored cosmic realities. According to some interpretations, the Casimir Effect is related to the cosmological constant problem, which is the huge discrepancy between the expected and observed values of the vacuum energy. To put it briefly, one of the main pillars of our conception of reality is the Casimir Effect.

Practical Applications of Casimir Effect: MEMS/NEMS

Despite its abstract nature, the Casimir Effect has real-world applications, particularly in the field of micro- and nano-engineering. Over the past 20 years, engineers and researchers have found that Casimir forces are now a significant factor that can determine whether a system succeeds or fails as it gets smaller to microscopic and nanoscopic scales [3]. Devices having moving parts the size of micrometers or nanometers are known as MEMS (Micro-Electro-Mechanical Systems) and NEMS (Nano-Electro-Mechanical Systems). Sensors, accelerometers, actuators, and other parts of smartphones, medical equipment, and aerospace systems all employ them. These gadgets frequently consist of small cantilevers, plates, or levers that are hung above a substrate.

Casimir forces are powerful enough to bring components together at this distances. This results in stiction, a condition in which components that are meant to move separately become stuck to one another and cease to function. Because of this significant form of failure in MEMS, engineers have been forced to start including quantum mechanical phenomena into the design and testing of these devices. One of the difficulties is that, for actual devices, it is not always simple to forecast the Casimir force. Perfect, flat, parallel plates at zero temperature were used to obtain the original equations. However, real-world systems typically operate at room temperature or higher, have curved geometries, finite conductivity, and rough surfaces. More sophisticated models, such as the Lifshitz theory and numerical simulations employing boundary element techniques, are employed to address these complications. These aid in determining the true Casimir forces in particular designs.

Through material design, some efforts have begun to investigate ways to control or even inhibit it. One crucial approach is the use of layered materials, in which the Casimir force's behavior can be altered by engineering alternating thin films of metals and dielectrics. Through thorough theoretical modeling, researchers F.S.S. Rosa, D.A.R. Dalvit, and P.W. Milonni [4] showed in a seminal 2008 study that absorb multilayer structures—more especially, those composed of alternating metal-dielectric layers—could considerably lessen the Casimir force's magnitude and, in some cases, even change its nature. Their findings demonstrated that the sequencing, thickness, and absorption characteristics of the layers all affect the force's strength. Designing micro- and nanoscale devices that are less impacted by stiction is now possible thanks to this effort.

The Casimir force is essential to the dynamic behavior of MEMS/NEMS devices in addition to basic stiction. Pull-in instability, for instance, can occur in systems with movable components, such as micro-oscillators or cantilevers, when the attractive pressure builds up to the point where a structure abruptly collapses against a neighboring surface. This places limitations on these systems' mechanical stiffness, operating voltage, and resonance frequency. In order to preserve stability at sub-micron scales, the scientific community has found solutions by integrating Casimir force predictions straight into the design process. This includes choosing surface coatings, modifying geometries, and employing stiffer supports. The Casimir contribution in irregular device topologies is now frequently estimated using more sophisticated simulation techniques, such as those based on boundary element methods or finite-difference time-domain (FDTD) approaches. These advancements demonstrate how quantum fluctuations, which establish performance thresholds in next-generation micro and nanosystems, have evolved into a useful engineering variable.

Applications for Casimir force in sensing have also been employed. Small positional adjustments can result in detectable force changes since force is sensitive to distance. This can be applied to the development of extremely sensitive switches or detectors. Additionally being investigated are resonators based on the Casimir Effect, in which vacuum oscillations help move mechanical parts without the need for external power. We are starting to confront and accept forces that defy the laws of classical quantum dynamics as we venture farther into the nanoworld. Previously a theoretical concept, engineers and designers now have to consider the Casimir Effect. It serves as both a problem and an opportunity, serving as a reminder that just because we have created something practical, the weird laws of physics still exist.

Casimir Effect and its Future

The Casimir Effect's prospective uses are probably going to go well beyond the MEMS/NEMS devices of today as scientists continue to improve their knowledge and manipulation of it. The creation of frictionless or nearly frictionless components is one exciting avenue. The components could be suspended and guided without ever coming into contact with one another if Casimir repulsion can be consistently accomplished using engineered materials, multilayer stacks, or metamaterials. This would remove wear and significantly extend the life and sensitivity of nanoscale gear, particularly in settings where lubrication is challenging or impossible, such as clean room robots or space.

Casimir-based actuation and energy harvesting represent yet another fascinating frontier. New types of extremely efficient switches, resonators, or signal amplifiers may be possible with devices that purposefully use Casimir forces to provide controlled motion without the need for external voltages or moving mechanical components. Despite being weaker than conventional mechanical interactions, the force can be used in situations where conventional actuation mechanisms are ineffective due to its predictability and persistence at nanoscale separations. Particularly for precision applications like quantum sensing and biological detection, researchers have already started creating parametric amplifiers and frequency-sensitive sensors that incorporate Casimir interactions as essential design components.

A more comprehensive change in the way engineers approach quantum-scale design is encouraged by the ongoing research on Casimir forces. In order to overcome design constraints and transform quantum effects into useful tools, it is increasingly important to comprehend the subtle forces resulting from vacuum fluctuations as we enter the era of quantum technologies. At the nanoscale, the distinction between engineering and physics is becoming more hazy, and the Casimir Effect has come to represent how even the most subdued natural forces may spur creativity.

Conclusion

The Casimir Effect serves as a reminder that even seemingly insignificant things can have significant power. Although it began as an odd concept in theoretical physics, engineers and designers now actively cope with it—or even exploit it—when creating small machines. Forces like the Casimir force, which originates from quantum fluctuations, become crucial in daily physics and engineering as technology becomes more accurate and smaller. Ignoring the Casimir force is not an option in MEMS and NEMS, where distances are measured in micrometers and nanometers, respectively. More than that, though, knowing it allows us to manage it, mold it, and perhaps use it to address issues that traditional tools are unable to tackle. The ability to pay attention to the smallest forces around us—including those emanating from seemingly space—will determine the direction of technology in the future, not the size of the machines.

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Siddharth Mishra, Prachi Pratyasha Das
5th Sem, Dept. of EE

Sun-powered device extracts lithium without wrecking the environment

A novel experimental technique for lithium extraction from brine and seawater is anticipated to be more sustainable than current approaches. The extraction of lithium for batteries, essential for the electric vehicle revolution and stabilizing renewable energy supply, is environmentally detrimental. However, an experimental solar-powered technique that generates both potable water and lithium could enhance sustainability. Currently, the majority of lithium is extracted from subterranean brine deposits in the Andes. The brine is concentrated through evaporation in open-air ponds over several months, and the subsequent extraction of lithium carbonate from the concentrated brine necessitates substantial amounts of fresh water. Furthermore, as the brine is extracted from the reservoirs, freshwater from the overlying rocks may descend to compensate, resulting in a decline in the water table. Mining significantly affects the water supply.

Source: newscientist.com

Shocking Facts On Food Waste

Food waste is a widespread issue that is not limited to wealthy countries. Given that one-third of all food meant for human consumption is lost or wasted, it is alarming to consider that over 800 million people are currently suffering from severe malnutrition. Food waste has a detrimental impact on nutrition, food security, the economy, and the environment. More than 40% of losses in affluent nations happen at the retail and consumer levels, whereas 40% of losses in underdeveloped nations occur during the post-harvest and processing phases. About the same quantity of food is wasted or lost annually in developed and developing nations (670 and 630 million tons, respectively).

Here are some startling figures on food waste:

Food waste typically consumes up to 21% of freshwater, 19% of fertilizers, 18% of cropland, and 21% of landfill volume when all resources used to grow food are taken into account. Nine billion people could consume the water needed to generate the wasted food, which amounts to about 200 litres per person every day. Food wastage ultimately results in the loss of a fourth of the global water supply, equivalent to approximately ₹14.3 lakh crore in water squandered as uneaten food.

Consumer waste ranges from 6 to 115 kilograms annually across different regions. Every year, almost one-fifth of the 1.3 billion tons of food produced for human consumption—worth ₹83 lakh crore—is lost or squandered. Three billion people could be fed with this food. About 4.4 gigatonnes of greenhouse gas emissions are caused by food loss and waste each year; if food loss were a nation, it would be the third-largest emitter of greenhouse gases globally. Eight hundred seventy million people could be fed if just 25% of the food that is currently lost or wasted worldwide could be rescued. Therefore, effectively addressing the global problem of food waste will continue to be extremely challenging in the years to come.

Source: https://earth.org/facts-about-food-waste/

Fingerprint Image Classification using Fuzzified FLANN

Abstract – *This work presents a novel hybrid classification approach integrating Fuzzy Logic with the Functional Link Artificial Neural Network (FLANN) model, optimized using Genetic Algorithms (GA) for fingerprint classification. The proposed methodology enhances the classification performance by fuzzifying the parameters of the FLANN model into linguistic levels (Low, Medium, High) using various membership functions—triangular, trapezoidal, and Gaussian. The extracted fingerprint features, obtained via a Gabor filter bank across four orientations (0°, 45°, 90°, and 135°), form a 152-dimensional feature vector that undergoes functional expansion based on trigonometric, Chebyshev, and Legendre polynomial basis functions. Fuzzified parameters are subsequently optimized using Genetic Algorithms, which reduce mean square error through elite selection, mutation, and crossover processes. Experimental results demonstrate that the Fuzzy-GA-FLANN model significantly improves classification accuracy and execution time compared to conventional Genetic-FLANN models. Notably, the Chebyshev-based Fuzzy-GA-FLANN model achieves 98% accuracy with reduced computation time, highlighting its robustness and efficacy for biometric fingerprint classification tasks.*

Keywords *– FLANN, Fuzzy Logic, Genetic Algorithm, Fingerprint Classification, Feature Extraction.*

I. Introduction

Fingerprint classification plays a vital role in biometric authentication by categorizing fingerprint patterns into classes such as arch, loop, and whorl. This classification helps reduce search time and improves identification efficiency in large-scale databases. However, automatic fingerprint classification is challenging due to issues like poor image quality, non-linear distortions, and ambiguous ridge patterns. Fig. 1 shows the fine fingerprint classes according to the Henry System.

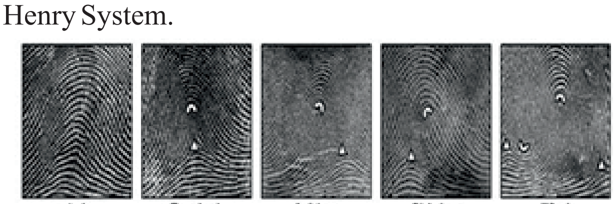

Fig 1. Five fingerprint classes of Henry System

To overcome these limitations, this research introduces a hybrid model that integrates Functional Link Artificial Neural Networks (FLANN) with fuzzy logic and evolutionary optimization algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The goal is to enhance classification performance while addressing uncertainty and computational inefficiency in traditional methods.

Core Techniques and Research Objectives: The Functional Link Artificial Neural Network (FLANN) enhances learning by expanding input features into a higher-dimensional space using basis functions like trigonometric, Chebyshev, or polynomial expansions. This transformation enables the network to capture complex relationships with a simplified structure. Fuzzy logic is incorporated to manage uncertainty in fingerprint features. It assigns linguistic values—Low, Medium, and High—using membership functions such as triangular, trapezoidal, or Gaussian. This approach improves the model's interpretability and robustness.

To fine-tune the network parameters, optimization algorithms are employed. Genetic Algorithm (GA) evolves solutions over generations through selection, crossover, and mutation, while Particle Swarm Optimization (PSO) simulates swarm intelligence to discover optimal parameter configurations efficiently. These optimization techniques complement the learning ability of FLANN and the flexibility of fuzzy logic.

This research aims to design a robust fingerprint classification model that can accurately classify input patterns under noisy and uncertain conditions. The model leverages functional expansion, fuzzy reasoning, and optimization to achieve better generalization, faster convergence, and improved classification accuracy.

II. Literature Survey

1. Existing Fingerprint Classification Methods

Fingerprint classification [1-5] improves search efficiency by grouping patterns into predefined classes like arch, loop, and whorl. Traditional rule-based methods rely on visual features such as ridge flow and singular points, but are sensitive to noise and distortions. Statistical approaches like PCA and LDA [6,7] improve accuracy but often fail with non-linear variations. Neural network-based methods, including CNN and FLANN, offer improved learning but demand more computational resources. Recent hybrid models integrating fuzzy logic and optimization techniques demonstrate greater adaptability in real-time systems.

2. Applications of FLANN in Classification

FLANN, a single-layer neural network [8-10], enhances learning by functionally expanding input data using trigonometric, Chebyshev, or Legendre polynomials. It offers a simple yet powerful architecture for complex classification tasks. FLANN is widely used in biometric authentication, medical diagnosis, speech recognition, and industrial monitoring. Due to its efficient convergence and scalability, FLANN is frequently combined with optimization algorithms [11,12] to form adaptive hybrid models.

3. Fuzzy Logic in Neural Networks

Fuzzy logic adds robustness to neural networks by representing input data with linguistic variables like Low, Medium, and High through membership functions. This improves the network's ability to handle uncertainty and overlapping classes. In Fuzzy Neural Networks (FNN) [13-15], fuzzy inputs are processed and mapped to either fuzzy or crisp outputs. Hybrid models such as Fuzzy-GA-FLANN or Fuzzy-PSO-FLANN [16,17] benefit from the interpretability of fuzzy systems and the adaptive learning of neural networks, achieving better accuracy and resilience.

4. Optimization Algorithms in Neural Network Training

Optimization algorithms refine neural networks by minimizing prediction errors. Traditional gradient-based methods like Stochastic Gradient Descent SGD are efficient but may struggle with complex loss surfaces. Evolutionary algorithms like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) [18-20] provide alternatives by exploring diverse solutions simultaneously. GA uses natural selection strategies, while PSO leverages swarm intelligence for rapid convergence. These algorithms, when integrated with fuzzy systems or FLANN, enhance the overall learning capacity and generalization of the network.

III. Methodology

The Hybrid Fuzzified FLANN Model is a comprehensive fingerprint classification technique that combines the strengths of Functional Link Artificial Neural Network (FLANN), fuzzy logic, and Genetic Algorithm (GA) optimization. This integration enhances both the precision and robustness of the classification process.

The model starts with the acquisition of fingerprint images, followed by feature extraction using a Gabor filter bank at orientations of 0°, 45°, 90°, and 135°. These filtered images yield a 152-dimensional feature vector that represents the essential texture and ridge details of each fingerprint. These feature vectors are then input into the FLANN classifier for functional expansion, utilizing mathematical basis functions such as trigonometric, Chebyshev, or Legendre polynomials to transform linear data into a richer nonlinear representation.

After functional expansion, fuzzification is applied to convert numerical inputs into fuzzy linguistic variables (Low, Medium, High) using membership functions such as triangular, trapezoidal, or Gaussian. This step provides the system with the ability to interpret uncertain or imprecise input values. Defuzzification using the centroid method transforms these fuzzy sets back into precise numerical values for further processing.

To enhance the accuracy of the system, the model incorporates Genetic Algorithms for optimization [12]. GA initializes a population of potential weight configurations, evaluates them using Mean Square Error (MSE) as a fitness function, and iteratively improves them using selection, mutation, and crossover operations. The result is an optimized set of parameters that are then fed back into the FLANN for final classification.

The hybrid Fuzzy-GA-FLANN model shows improved performance over standard FLANN and Genetic-FLANN systems. For instance, using Chebyshev basis functions and triangular membership functions, the system achieved 94% classification accuracy in just 549 seconds. These results validate the model's suitability for biometric applications where precision, adaptability, and computational efficiency are essential.

The FLANN as a Classifier FLANN is a computationally efficient neural network model that operates without hidden layers. It achieves nonlinear classification by applying functional expansions to the input data. For fingerprint classification, the 152-dimensional feature vector is expanded using basis functions, then processed by multiplying with a set of initialized weights. These values are summed in an adder unit and passed through a threshold function to produce the output.

The classification process involves evaluating the output against the desired target and calculating the error. This error is used to iteratively update the network weights using the equation 1:

$$W_j(k+1) = W_j(k) + \mu \cdot e(k) \cdot x_j \quad \text{................. (1)}$$

where W_j is the weight, μ is the learning rate, e(k) is the error, and x_j is the input feature. This process continues until the error is minimized, ensuring accurate classification.

The structure of Fuzzified FLANN Classifier is shown in Fig. 2. It is designed to handle the uncertainty and variability often present in biometric data. It incorporates fuzzy logic principles to convert crisp input values into fuzzy variables. These inputs are categorized into three fuzzy sets: Low, Medium, and High, using membership functions. Once fuzzified, the data proceeds through the FLANN network, where it is weighted, aggregated, and passed through a thresholding function.

To further refine the network's performance, the weights and input parameters can be optimized using either Genetic Algorithms or Particle Swarm Optimization (PSO). This dual-layer optimization enhances both the learning capability and classification reliability of the model.

The algorithm of FLANN as a Classifier is described below:

Step 1: Input the 152×1 feature vector.

Step 2: Perform functional expansion using trigonometric, Chebyshev, or Legendre basis functions.

Step 3: Multiply expanded features by initialized weights.

Step 4: Sum the weighted features and pass through the threshold function to generate the output.

Step 5: Calculate the error using $e(k) = y(k) - \hat{y}(k)$.

Step 6: Update weights using $W_j(k+1) = W_j(k) + \mu \cdot e(k) \cdot x_j(k)$.

Step 7: Repeat steps until the error converges to an acceptable level.

The Fuzzy Membership Function Formulation logic enhances neural network interpretability by transforming crisp values into fuzzy sets. Different types of Fuzzy membership functions are shown in Fig. 3. Common membership functions include:

1. Triangular MF, defined by three parameters (a, b, c), offering simplicity and fast computation.
2. Trapezoidal MF, defined by four parameters (a, b, c, d), allowing a flat region for better coverage.
3. Gaussian MF, defined by a mean (a) and standard deviation (σ), providing smooth transitions.

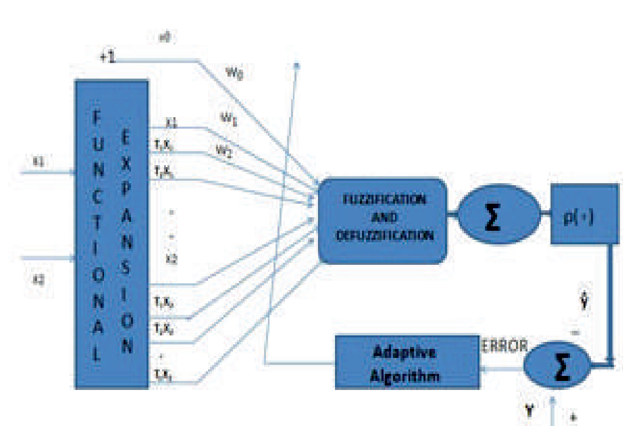

Fig. 2. The structure of fuzzified FLANN classifier

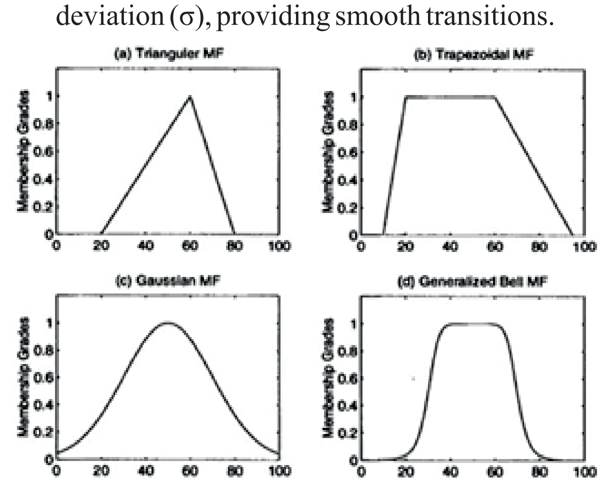

Fig. 3. Various types of Fuzzy membership functions

Each expanded input feature is mapped into fuzzy levels (Low, Medium, High) based on its degree of membership, facilitating a more flexible and adaptive classification system.

In this phase, each functionally expanded input is fuzzified using the selected membership functions. This mapping into multiple fuzzy sets allows the system to process ambiguous and noisy data more effectively. The fuzzy values are later defuzzified to produce crisp outputs for classification.

This step enhances the system's ability to deal with real-world biometric data that often contain inconsistencies or incomplete patterns, thus improving overall classification reliability.

The proposed Fuzzy-Genetic-FLANN model is shown in Fig. 4. It integrates four major components: feature extraction using Gabor filters, functional expansion via FLANN, fuzzification of expanded features, and optimization using GA. Fingerprint images are filtered in four directions to extract texture and ridge patterns, forming the feature vector. The FLANN expands these features non-linearly. Fuzzy logic assigns linguistic terms to each feature, and GA optimizes the network's parameters to achieve high classification performance. This combined approach allows precise and reliable classification in biometric security systems.

The algorithm of Fuzzy-Genetic-FLANN is described below:

Step 1: Collect and pre-process fingerprint images

Step 2: Apply Gabor filters and generate the 152-dimensional feature vector.

Step 3: Expand the feature vector using basis functions.

Step 4: Fuzzify the expanded inputs using selected membership functions.

Step 5: Initialize a population for GA optimization.

Step 6: Compute fitness for each chromosome using MSE (Mean Square Error).

Step 7: Select top 20% as elite group, apply mutation on 50%, and perform crossover on 30%.

Step 8: Repeat the optimization process until convergence.

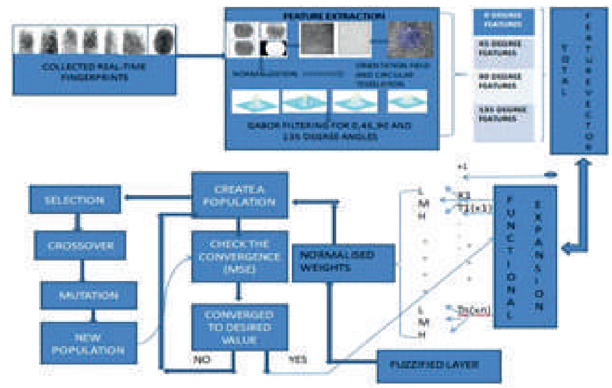

Fig. 4. Structure of the proposed hybrid Fuzzy-GA- FLANN model

Step 9: Use the best performing chromosome to update the FLANN for final classification.

The Fuzzy-PSO-FLANN model substitutes GA with PSO for optimization. In this setup, particles represent candidate solutions (weight vectors) that navigate the solution space. Each particle updates its position based on its own experience (personal best) and the collective experience of the swarm (global best). PSO enhances convergence speed and accuracy, offering a viable alternative for parameter tuning.

The algorithm of Fuzzy-PSO-FLANN as described below:

Step 1: Acquire fingerprint images and perform feature extraction.

Step 2: Functionally expand the features using FLANN.

Step 3: Apply fuzzification using chosen membership functions.

Step 4: Initialize a swarm of particles representing different weight vectors.

Step 5: Evaluate particle fitness using MSE.

Step 6: Update each particle's velocity and position using personal best and global best values.

Step 7: Iterate until a termination criterion is met.

Step 8: Use the best-performing particle's parameters for classification using the FLANN model.

IV. Result and Analysis

The Fuzzy-Genetic-FLANN model achieved 98% classification accuracy with 621.2 seconds of computation time using the Chebyshev basis function. Comparatively, Genetic-FLANN reached 94%

accuracy but required over 44,000 seconds. The Fuzzy-GA-FLANN model using trigonometric expansion and triangular membership functions achieved 94% accuracy in 549.73 seconds.

The dataset consists of 50 real-time fingerprint images collected from individuals at Silicon University, Odisha. Each fingerprint is categorized according to the Henry classification system (e.g., Whorl, Arch, Loop). Feature extraction involves preprocessing steps including orientation field estimation, core point detection, circular tessellation, and Gabor filtering at 0°, 45°, 90°, and 135° angles. Each fingerprint is represented by a 152-dimensional feature vector with an assigned class label.

The primary dataset of 50 fingerprint samples was used. Key steps include feature extraction via Gabor filters, creation of feature vectors, and classification using FLANN. Fuzzification was applied using triangular, trapezoidal, and Gaussian membership functions, followed by optimization using GA and PSO. Metrics such as classification accuracy, mean square error, and execution time were used for evaluation.

Performance Metrics

1. Classification Accuracy: Indicates the percentage of correctly classified fingerprints.
2. Mean Square Error (MSE): Measures the average squared difference between predicted and actual outputs.
3. Execution Time: Assesses model efficiency.

Table 1.Output of Genetic-FLANN and Fuzzy-Genetic-FLANN showing classification accuracy and execution time

S. N.	Flann Basis Function	Genetic-FLANN		FUZZY-Genetic-FLANN	
		Classification Accuracy in %	Execution time(in sec)	Classification Accuracy in %	Execution time (in sec)
1	Trigonometric	94	4.479 e+04	94	549.73
2	Chebyshev	90	1.066 e+03	98	621.2
3	Polynomial	94	2.963 e+04	98	4.5e04

4. Confusion Matrix: Evaluates classification performance per class using true/false positives and negatives.

The results of FLANN Classifier achieved 100% accuracy across individual and combined directional features with execution times between 19.3 and 64.16 seconds. Although highly accurate, performance depends on parameter tuning such as the stabilizing factor μ. Lacking optimization, FLANN is sensitive to initialization and less adaptive to noisy inputs.

The results of Genetic-FLANN achieved 90–94% accuracy with high execution times (up to 44,790 seconds). In contrast, Fuzzy-Genetic-FLANN improved accuracy to 98% using Chebyshev basis functions with significantly lower execution time (621.2 seconds). The inclusion of fuzzification and optimized GA processing enabled better adaptability and performance. Table 1 summarizes this result.

The results of PSO-FLANN improved optimization over basic FLANN but lacked fuzziness. Fuzzy-PSO-FLANN added fuzzified input representation (Low, Medium, High) and achieved better accuracy and lower MSE. It demonstrated enhanced robustness and efficiency suitable for real-time scenarios. Table 2 describes the Fuzzy-GA-FLANN performance using different membership function.

Table 2.Output of Fuzzy-GA-FLANN (using trigonometric FLANN for different Mfs)

S. N.	Fig. 1. Membership Function	M.S.E	Classification Accuracy	Execution Time in Seconds
1	Trapezoidal	0.032	92%	578.46
2	Gaussian	0.0456	90%	551.29
3	Triangular	0.0365	94%	549.73

The Comparison of Results Fuzzy-integrated models consistently outperformed non-fuzzy counterparts. While FLANN was accurate, it lacked adaptability. Genetic-FLANN improved this but suffered from high computation time. Fuzzy-GA-FLANN and Fuzzy-PSO-FLANN offered high accuracy with optimized efficiency, making them better suited for biometric systems. The Fuzzy-GA-FLANN Model using different membership functions are shown in Fig. 5(a) - 5(c).

Integrating fuzzy logic and optimization algorithms into FLANN significantly enhanced performance.

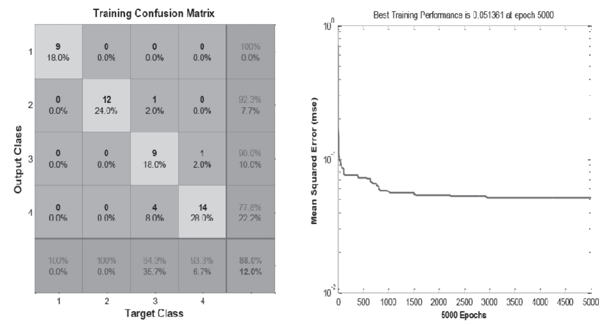

Fig 5(a). Trapezoidal Trigonometric FLANN

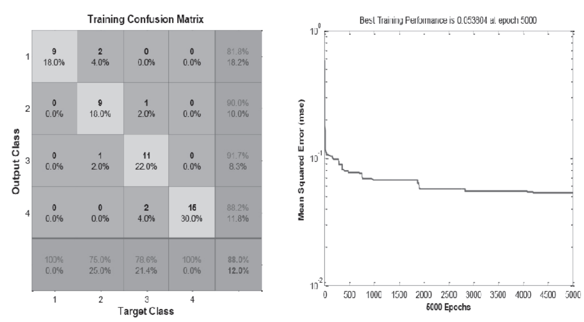

Fig 5(b).Gaussian Trigonometric FLANN

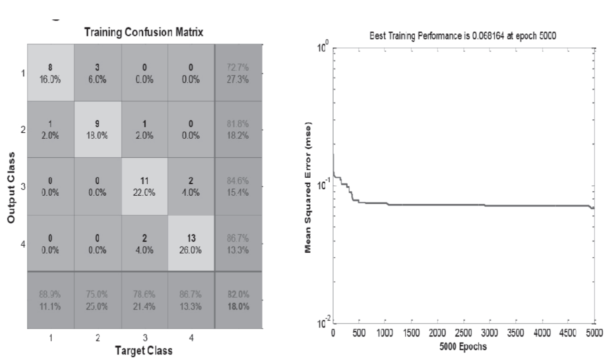

Fig 5(c).Triangular Trigonometric FLANN

Fuzzification enabled better handling of uncertain data, and GA/PSO facilitated efficient parameter tuning. Among all configurations, Fuzzy-GA-FLANN with Chebyshev expansion provided the best accuracy-time trade-off, reinforcing the hybrid model's suitability for robust, real-time fingerprint classification.

V. Conclusion & Future Work

The integration of Functional Link Artificial Neural Networks (FLANN) with Genetic Algorithms (GA) presents a robust and efficient framework for solving complex classification problems. FLANN's flat architecture, combined with functionally expanded inputs, reduces computational overhead, while GA enhances learning by optimizing network weights through evolutionary strategies. This hybrid model addresses limitations of weight sensitivity and convergence issues typical of traditional FLANN implementations.

Our study confirms that the hybrid Fuzzified FLANN model enhanced with GA delivers improved learning efficiency, classification accuracy, and adaptability to noisy or dynamic environments. The GA's population-based search enables broader solution exploration, leading to well-optimized parameters and superior system performance. This makes the model highly suitable for real-time and data-intensive applications such as signal processing, biometric authentication, and pattern recognition. The success of this hybrid framework underscores the potential of neuro-evolutionary systems in intelligent computing.

To further enhance the proposed model, future research can explore advanced fuzzy logic systems like Type-2 Fuzzy Sets or ANFIS for better uncertainty management. Additionally, integrating multi-objective optimization techniques such as PSO, GWO, or hybrid GA-PSO could improve convergence and result diversity.

Expanding the model to other biometric modalities like iris, palmprint, or face recognition could broaden its applicability in multimodal authentication systems. Finally, real-time deployment on embedded platforms or FPGAs should be investigated to optimize computational efficiency for practical use. These improvements would further solidify the hybrid Fuzzy-GA-FLANN model as a scalable and intelligent solution for complex pattern recognition tasks.

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Sudevi Panda, Rishu Kumar,
K Raj Shekhar Reddy
Dept. of EE

The Faraday Lectures and Candle Burning….

The Christmas lectures for young people was founded by the famous English chemist Michael Faraday in 1825, and continue till today, as probably the longest series of continuous lectures delivered every year. These lectures were designed to make science accessible to the general public, including children.

In 1845, Faraday delivered six lectures on the physics and chemistry of a candle. These included detailed talks on the candle flame, its sources and structure, the brightness of the flame, the air necessary for combustion, the production of water from the combustion, the oxygen present in the air, and the nature of the atmosphere, other products from the candle, and coal gas respiration and its analogy to the burning of a candle.

A candle flame may seem commonplace, but the underlying physics is rather complicated. It's not immediately evident, but the fact is that solids and liquids do not burn - only gases and vapors do! Molten wax enters the wick by capillary action, gets heated up, and evaporates around the perimeter of the wick. This hydrocarbon wax vapor is what burns and produces light and heat. The characteristic shape of the candle flame is due to buoyancy-driven gas flows surrounding the flame - hot air adjacent to the flame rises, 'pulling' the edges of the flame with it. Cold air takes its place below, and convection currents are set up around the flame. There is always more to it than meets the eye!

(Content excerpted from Wikipedia and other available web sources)

P.S. Out of curiosity, would the candle retain this characteristic shape in zero or microgravity?

Dr. Jaideep Talukdar
Dept. of BSH

Publication Cell
Tel: 9937289499/8260333609
Email: publication@silicon.ac.in

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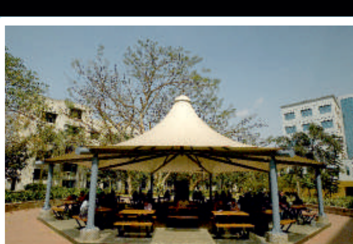

Silicon University, Odisha

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