Volume IV, Issue 3
January 2024

American Journal of **Electronics & Communication**

Society for Makers, Artists, Researchers and Technologists,
USA 6408 Elizabeth Avenue SE, Auburn, Washington 98092.
ISSN 2690-2087

Content

American Journal of Electronics & Communication

Sumit Kundu et. al., American Journal of Electronics & Communication, Vol. IV (3), 1-5

Detection of Citral in some lemongrass essential oil with copolymer composites based QCM Sensor

Sumit Kundu
Dept. of Textile Technology
Government College of Engineering and Textile Technology
Serampore, India
kundusumit565@gmail.com

Deepam Gangopadhyay
Dept. of Instrumentation and Electronics Engineering
Jadavpur University
Kolkata, India
deepamganguly@gmail.com

Mahuya Bhattacharyya Banerjee
Dept. of Computer Science and Engineering
Government College of Engineering and Textile Technology
Serampore, India
mahuyabanrjee@gmail.com

Shreya Nag
Dept. of Electronics and Communication Engineering
University of Engineering and Management
Kolkata, India
snshreya20@gmail.com

Runu Banerjee Roy
Dept. of Instrumentation and Electronics Engineering
Jadavpur University
Kolkata, India
runuroy@yahoo.com

Abstract*— Citral, a significant aldehyde monoterpene found in various kinds of lemongrass (Cymbopogon sp.), is used as an aromatherapy tool to decrease tension, anxiety, and depression, as well as a fragrance in soaps and other personal care items. Moreover, recent research has revealed that this substance has numerous important health benefits, including anti-oxidant, anti-inflammatory, anti-hyperglycemic, and anti-diabetic qualities, to mention a few. Citral is the major component of the lemongrass essential oil (LGEO). The percentage of citral found in commercially marketed LGEOs are quite fluctuating, therefore it is important to quantify the citral molecules in the commercially available LGEOs. In this study, a pioneering detection method for citral is presented using copolymerization of Methacrylic Acid and Styrene on the surface of a Quartz Crystal Microbalance (QCM) sensor. The fabricated sensor has yielded a high sensitivity of 0.0833 Hz/ppm with a commendable correlation factor (R^2) of 0.9648. The applicability of this sensor is further enriched by its large linear operating range of (50-600) ppm. The potential of the sensor was further investigated by discriminating four four distinct commercially available LGEO depending on Citral c oncentration, which has produced a high separability index of 0.9562 when analyzed through Principal Component Analysis. This QCM-based measurement technique enhances citral detection possibilities with promising results thereby further widening the application areas for QCM based measurement.

***Keywords*— Lemongrass Essential Oil, Citral, QCM, PCA**

I. Introduction

Since ancient times, therapeutic plants, often known as medicinal herbs, have been found and employed in traditional medical procedures. Cymbopogon citratus (commonly known as lemongrass) is one such plant that found its widespread application in various traditional medicine and other industrial applications based on its essential oil. Lemongrass essential oil (LGEO) can be extracted from the leaves and stems of species of Cymbopogon like Cymbopogon citratus, Cymbopogon flexuosus, Cymbopogon winterianus, Cymbopogon martinii, Cymbopogon nardus, and Cymbopogon refractus [1] by different methods such as steam distillation, hydro distillation (HD), microwave-assisted hydrodistillation (MAHD), and supercritical fluid extraction (SFE) with CO_2 [2]. The main ingredients of essential oils are terpenes, which are naturally occurring volatile molecules with a strong aroma. Citral, [3,7-dimethyl-octa-2,6-dienal] is a monoterpene aldehyde which is the major component of LGEO comprised of two geometric isomers geranial (transcitral, citral A) and neral (cis-citral, citral B) [3-4]. The molecular structure of citral is shown in Fig1. It is found in many studies [1,2,4] that various LGEO contains geranial (20-40%), neral (15-35%), geraniol (8-20%), limonene (5-8%) and linalool (2-5%) as main components. Due to its distinctive lemon fragrance, citral has become a flavouring agent of significant importance, and a widely utilized raw material for the pharmaceutical, food, perfume, and cosmetics sectors [2, 22]. Apart from its several industrial uses citral has antimicrobial, antioxidant, anti-inflammatory, cardiovascular, antihyperglycemic, antidiabetic and antitumour properties [5-10]. The citral content of LGEO is typically used to assess the quality of the oil and must be at least 75% to be regarded as a high-quality product [24]. Admissible daily intake for citral is 0.5 mg/Kg [23].

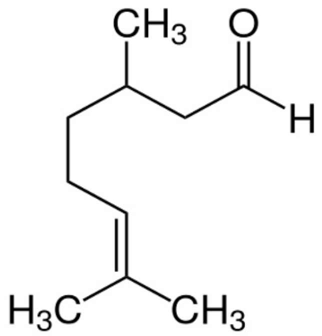


Fig.1. Molecular structure of citral.

To evaluate the quality of commercially available LGEO, the methods for its proper detection and quantification have become significant. Several chromatography and spectrometry techniques namely gas chromatography-ion mobility (GC-IMS), gas chromatography-mass spectroscopy (GC-MS), gas chromatography with flame ionization detector (GC-FID), liquid chromatography (LC) and Fourier Transform Infrared Spectroscopy (FTIR) have been used for this purpose [13-15]. However, these detection methods are reliable but they are frequently time-consuming and expensive, and when the kind of essential oil varies, they may require expensive modifications to the acquisition equipment. Additionally, these systems demand highly qualified personnel for reliable operations. On the contrary, unconventional methods like QCM-based aromatic gas detection techniques have the advantages of being lightweight, affordable, and durable with specialized, extremely sensitive, and precise measuring capabilities [16]. The sensing component of QCM has undergone a number of advancements in recent years, which have greatly expanded the application fields it may be used. These areas now include drug identification in pharmaceutical applications and quality assessment of commercially available foods and drinks [17-19]. A QCM sensor functions by changing the resonance frequency (f_0) of an AT-cut quartz crystal as the quantity of gas sample adsorption varies. According to Sauerbrey's equation [20] which is shown in eq (1), the variation in frequency (Δf) and the quantity of mass deposited (Δm) on the surface are linearly related.

$$\Delta f = -\frac{2 f_0^2}{A\sqrt{P_q Q_q}} \Delta m \quad (1).$$

Where:

f_0 : Resonant frequency of the fundamental mode (Hz)

Δf : normalized frequency change (Hz)

Δm : Mass change (g)

A : Active crystal area (Area between electrodes, cm^2)

P_q : Density of quartz (2.648 g/cm^3)

Q_q : shear modulus of quartz (2.947×10^{11} $g{\cdot}cm^{-1}{\cdot}s^{-2}$ for AT-cut crystal).

The sensing procedure comprises passing a stable, inert environment over the coated sensor surface while a regulated flow of a gas mixture containing the target analyte is being passed through. The analyte is adsorbed on the surface of the coated sensor during this process and frequency variations are seen for a while before stabilizing. The adsorbed gas is then released in a brief purging session. After being calibrated, the developed sensor can be used again for measurements with great accuracy [21]. The system's effectiveness depends on the conception of suitable coating materials for the crystal surface that can discriminate the target analyte from a mixture of gases originating from a source.

The proposed sensor has been developed by a polymer-based coating using Methacrylic Acid and Styrene as monomers and Di vinyl benzene as co-polymer. The target analyte's propensity to attach to the adsorption sites on the polymer chain is increased by using tung oil during polymerization. The ideal ratio of monomers to co-polymer and the most suitable coating thickness for the sensor surface have both been investigated in order to optimize coating properly. Based on the concentration of citral, the developed sensor was used to differentiate between four different LGEO samples using PCA.

II. Experimental

A. Materials and reagents used

Methacrylic acid (MA), Styrene, Di-vinyl-benzene (DVB), Tung Oil, and Ethanol were acquired from Sigma Aldrich in India. Four distinct LGEO samples and quartz crystal with silver-plated AT-cut 10 MHz sensors were purchased from the neighborhood market. The highest analytical grade was employed for each and every component.

B. Sensor development

Pure ethanol was used to clean the surface of bare quartz crystals, which were then dried and placed in a desiccator to prepare the sensor. The coating material has been prepared using various mixtures of MA, Styrene, and DVB with Ethanol as a solvent. In TABLE I, the combinations and frequency deviation for each of them has been presented. The sensor layer on the crystal surface has been set by using an easy drop-coating method. The coated sensor was placed in a temperature-controlled oven at 85ºC for 25 minutes in order to polymerize it.

C. Measurement Setup

Static headspace sampling methodology was used in the present study of QCM-based measurement. The sensor was inserted into a 100 cc Teflon-coated airtight chamber. The analytes were injected into the sensor chamber through a glass syringe at different concentrations. The flow of analytes into the chamber was managed by regulators. The sensor was excited by a high frequency generator using a Schmitt trigger. A microcontroller chip called the Atmega-328p has been used to accumulate data. A computer was used to process and store the generated data. The temperature and humidity were both kept constant throughout the whole experiment. After each measurement, the adsorbed analytes were released by using an air purging technique, after which the sensor returns to its baseline frequency.

D. Characterization of the Sensing Film

Fourier-transform infrared spectroscopy and scanning electron microscopy were used to analyze the sensor layer that was placed on the surface of QCM. The polymer sample was created in a glass vial for FTIR analysis and upon polymerization, was crushed into a powder using a mortar and pestle. In a 1:1 ratio, potassium bromide (KBr) was thoroughly combined with the powdered sample before being finely ground once more. This fine powder mixture was dried at 105°–115°C for two hours, and then the sample was palletized using a pallet-forming die by exerting a force of around 4 tons under several mm Hg of vacuum. The pallet's formation required some time. Fourier transform infrared spectroscope (L160000F, Perkin Elmer Inc, USA) with two temperatures stabilized DTGS (deuterated triglycine sulfate) detectors and standard optical system with KBr windows for data collection over a spectral range of 8,300 – 350 cm^{-1} at the best resolution of 0.5 cm^{-1} were made. To account for infrared light scattering losses, the background measurement was performed using only a pallet of KBr (no sample), after which the prepared pallet was placed on the pallet holder. With a 15 kV acceleration voltage, a scanning electron microscope (ZEISS) was used to examine the surface morphology of the sensor film.

III. Results and Discussion

A. Ratio Optimization

Ten distinct sensors, designated CT1 to CT10, have been created by altering the amounts of the reagents MA, styrene, DVB, tung oil, benzoyl peroxide, and ethanol listed in TABLE I. It has been seen that the CT4 sensor has produced a superior response from CT1 through CT10 responses at a particular 300 ppm gas concentration. As a result, further study has been performed using the CT4 sensor.

TABLE I. DIFFERENT COMPOSITION OF METHACRYLIC ACID – STYRENE - DIVINYL BENZENE-TUNG OIL COPOLYMERS

Sample No.	Monomers and Co-polymers used						Freq Dev (Hz)
	MA (µL)	Styrene (µL)	DVB (µL)	Tung oil (µL)	Benzoyl peroxide (g)	(Ethanol) (mL)	
CT1	50	20	10	20	0.05	10	8
CT2	50	20	20	20	0.05	10	16
CT3	50	20	30	20	0.05	10	12
CT4 [a]	**50**	**30**	**20**	**20**	**0.05**	**10**	**24**
CT5	50	30	10	20	0.05	10	20
CT6	50	40	10	20	0.05	10	12
CT7	60	40	20	20	0.05	10	20
CT8	60	40	30	20	0.05	10	16
CT9	60	40	20	20	0.05	10	12
CT10	70	40	20	20	0.05	10	16

[a] Denotes the optimum combinations of the monomers and co-polymers used.

B. Optimization of coating thickness

The responses of five distinct sensors to a constant concentration of citral have been demonstrated in Fig 2. These sensors were created with five different amounts of coating drop. This has led to the conclusion that a coating thickness of 2.4 µL is the amount at which the largest frequency variation occurs. With this, an optimal coating level has been achieved.

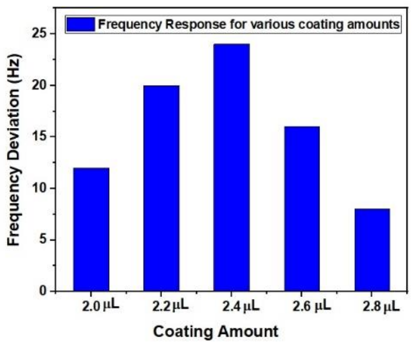


Fig.2 Coating amount optimization graph.

C. Sensitivity Analysis

Sensitivity dictates the response of the fabricated sensor in ppm. The optimized CT4 sensor has been exposed to varying concentrations of citral from (50-600) ppm using a calibrated glass syringe. The range of concentrations (in ppm) was calculated using eq (2), where V_1 and V_2 stand for the volume of the sensor chamber and the volume of the syringe respectively. S_1 and S_2 imply concentration (in ppm) of gas in the sensor chamber and the concentration (ppm) in the syringe respectively.

$$V_1 S_1 = V_2 S_2 \tag{2}$$

where,

V_1 = Volume of the sensor chamber

V_2 = Volume of syringe.

S_1 = Concentration (ppm) of gas in sensor chamber.

S_2 = Concentration (ppm) of gas in the syringe.

The sensitivity of CT4 was obtained by tracing its frequency response (in Hz) with respect to the range of concentrations (in ppm) of the target analyte starting from 50 to 600 ppm. Results are displayed in Fig.3. The sensitivity of CT4 sensor was calculated as 0.0833 Hz/ppm with a linear regression coefficient (R^2) of 0.9648. After each injection of the target analyte, the adsorbed gas on the surface of the sensor was removed through the standard air purging method, wherein the sensor was subjected to a continuous flow of fresh air, which removes the adhered target molecules thereby raising the working frequency of the crystal. The real time response profile for the fabricated CT4 sensor has been shown in Fig.4.

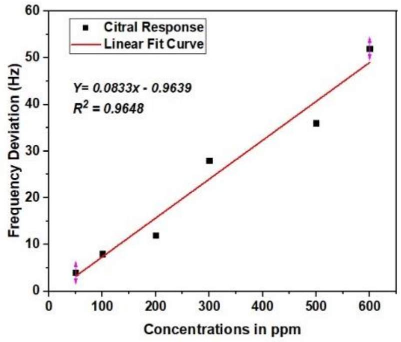


Fig.3. Sensitivity analysis curve

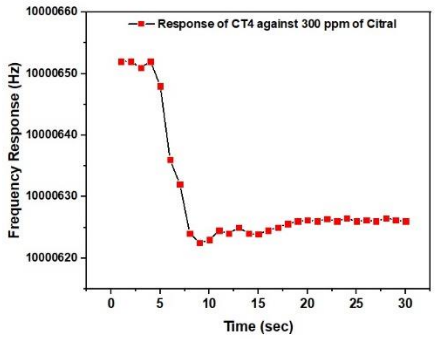


Fig.4. Real-time response profile of CT4 sensor for 300 ppm.

D. Fourier Transform Infrared Spectroscopy

The FTIR analysis of the synthesized methacrylic acid and styrene copolymer is illustrated in Fig. 5. As per the literature reference [25-26], the band observed at 1471 cm-1 corresponds to the symmetric stretching mode of the methyl group, while the distinctive features at 1895 cm-1 are indicative of carboxylic acid functionalities, representing simple carbonyl compounds featuring methyl (CH_3) bonds. Furthermore, the presence of a band at 2988 cm-1 can be attributed to the (vinyl) C-H stretch vibration originating from styrene.

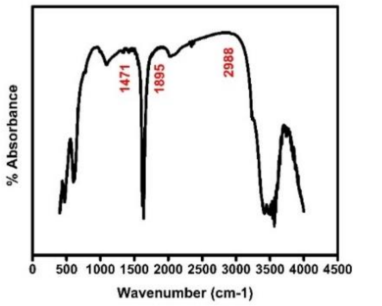


Fig.5. FTIR of synthesized methacrylic acid and styrene copolymer.

E. *Scanning Electron Microscopy*

The surface morphology of the bare crystal and crystal surface with sensing polymer has been shown in Fig 6(a) and 6(b). From the figures we can observe that the surface of the bare crystal is smooth, while the surface of the polymer is rough.

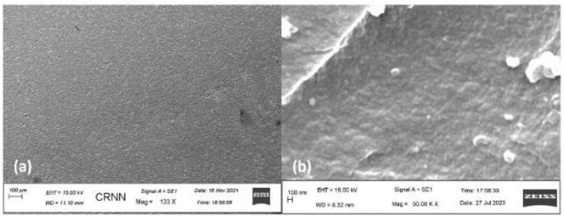


Fig.6. SEM images of (a) bare crystal and (b) methacrylic acid and styrene copolymer-based sensor.

F. *Repeatability, Reproducibility and Reusability*

Repeatability, reproducibility, and reusability are the three most significant criteria for a sensor. To evaluate the repeatability of the proposed sensor, different concentrations of citral were injected ten times at constant ambient conditions. Responses are presented in TABLE II. The maximum repeatability was attained at 600 ppm concentration (83.87%), while the average repeatability across all gas concentrations was 82.6%. Five distinct CT4 sensors were fabricated for the examination of reproducibility, and they were repeatedly exposed to the injected analyte. According to TABLE II, a maximum reproducibility of 80.92% was achieved at 300 ppm of injected citral vapor. Over the course of 80 days, static headspace sampling of the target gas was carried out under identical conditions at regular intervals. According to the response, which is shown in Fig. 7 the sensor is stable and reusable for a period above two months because the frequency variation is 12% on the 80th day from the response on the first day.

TABLE II. REPEATABILITY AND REPRODUCIBILITY RESULTS WITH 95% CONFIDENCE INTERVAL FOR CT4 SENSOR

Citral concentration (ppm)	Repeatability		Reproducibility	
	Rept (%)	***CI***	***Repd (%)***	***CI***
50	82.12	±3.99	80.23	±4.67
100	82.37	±4.65	79.98	±4.45
200	83.15	±5.43	80.26	±5.91
300	81.98	±4.97	80.92	±5.93
500	82.19	±5.32	79.95	±6.56
600	83.87	±5.86	80.73	±8.06
800	82.56	±8.96	80.58	±9.89

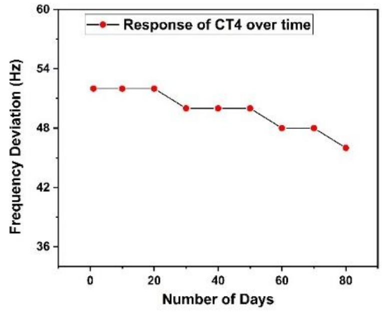


Fig.7. Reusability profile of CT4 sensor against citral.

G. *Study of Limit of Detection*

The limit of detection (LoD) of a sensor is another significant phenomenon. It is the smallest quantity of target gas that can be quantitatively measured and detected. It is based on the linear calibration curve's slope and the response's standard deviation (σ) as determined by a number of measurements (N). Mathematically it is expressed as,

$$\text{LoD} = 3.3\,\sigma / S \tag{3}$$

Based on eq (3), LoD was found at 7.15 ppm, which is the lowest limit of detection with the proposed measurement setup.

H. *Principal Component Analysis (PCA)*

Principal Component Analysis (PCA) is a statistical technique that is essential for data exploration because it transforms multidimensional data into coordinates that optimize variance while decreasing correlation in the dataset [18]. Every data point X_n is projected onto a scalar value $U_1^T X_n$. The mean of the projected data is UX' where X′ is the sample set mean given by,

$$X' = \frac{1}{N}\sum_{n=1}^{N} X_n \tag{4.1}$$

And the variance of the projected data is given by,

$$\frac{1}{N}\sum_{n=1}^{N}\{U_1^T X_n - UX'\}^2 = U_1^T S U_1 \tag{4.2}$$

Where S is the data covariance matrix defined by

$$S = \frac{1}{N}\sum_{n=1}^{N}(X_n - X')\,(X_n - X')^T \tag{4.3}$$

The biggest variance is seen in the first principal component, and this variance increases with each successive component. Two principal components, PC1 and PC2, or the first and second principal components, respectively, have been extracted from the dataset in this work, as shown in Fig. 8. In comparison to all other PCs, PC1 has been discovered to be 99.9993%, whereas PC2 is 0.0002% with a separability index of 0.9562.

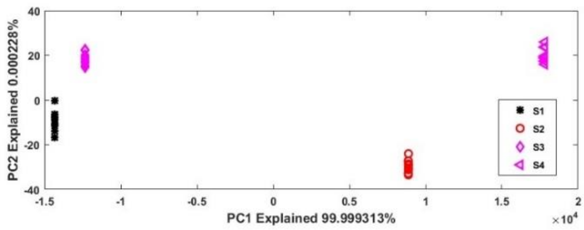


Fig.8. PCA Plot with 4 different concentrations of lemongrass essential oil.

IV. Conclusion

This study has introduced an innovative citral detection method, leveraging the copolymerization of Methacrylic Acid and Styrene on a Quartz Crystal Microbalance (QCM) sensor. The fabricated sensor has demonstrated exceptional sensitivity, registering at 0.0833 Hz/ppm, with a commendable correlation factor (R^2) of 0.9648. Furthermore, the sensor's versatility is underscored by its broad linear operating range of (50-600) ppm. The potential of this sensor has been further substantiated by its ability to distinguish between four different commercially available LGEO samples based on their citral content. Principal Component Analysis revealed a high separability index of 0.9562, showcasing the sensor's proficiency in discriminating citral levels effectively. This innovative QCM-based measurement technique opens up exciting possibilities for citral detection, offering promising results that extend the application areas for QCM-based measurements. It not only addresses the pressing need for citral quantification in LGEO but also has the potential to revolutionize the way we measure and utilize citral in various industries, further advancing its multifaceted applications.

Acknowledgment

The authors would like to extend their sincere gratitude towards University of Calcutta, CRNN, and Prof. Gautam Pramanik, UGC DAE Consortium, Kolkata centre for the SEM and FTIR facilities.

References

[1] Oliveira, E. R. de ., Alves, D. S., Carvalho, G. A., Oliveira, B. M. R. G. de ., Aazza, S., & Bertolucci, S. K. V.. (2018). Toxicity of *Cymbopogon flexuosus* essential oil and citral for *Spodoptera frugiperda*. *Ciência E Agrotecnologia*, *42*(4), 408–419.

[2] Majewska, E., Kozlowska, M., Gruszczynska-Sekowska, E., Kowalska, D., & Tarnowska, K. (2019). Lemongrass (Cymbopogon citratus) essential oil: extraction, composition, bioactivity and uses for food preservation-a review. *Polish Journal of Food and Nutrition Sciences*, *69*(4).

[3] Saddiq, A. A., & Khayyat, S. A. (2010). Chemical and antimicrobial studies of monoterpene: Citral. *Pesticide Biochemistry and Physiology*, *98*(1), 89-93.

[4] Mirghani, M. E. S., Liyana, Y., & Parveen, J. (2012). Bioactivity analysis of lemongrass (Cymbopogan citratus) essential oil.

[5] He, L. L., Zhao, Y., Fan, L. M., Zhan, J. J., Tao, L. H., Yang, Y. H., ... & Ye, M. (2023). In vitro and in vivo antifungal activity of Cymbopogon citrates essential oils from different climate conditions against Botrytis cinerea. *Scientia Horticulturae*, *308*, 111544.

[6] Ali, M. M., Yusuf, M. A., & Abdalaziz, M. N. (2017). GC-MS analysis and antimicrobial screening of essential oil from lemongrass (Cymbopogon citratus). *International Journal of Pharmacy and Chemistry*, *3*(6), 72-76.

[7] Lisboa, F. P., Silvestre, W. P., Castro, J. O., Martins, G. V., Segabinazzi, L. G., Pauletti, G. F., & Dell'Aqua, J. A. (2022). In vitro antimicrobial activity of selected essential oils against endometritis-causing microorganisms in mares. *Journal of Equine Veterinary Science*, *110*, 103840.

[8] Mukarram, M., Choudhary, S., Khan, M. A., Poltronieri, P., Khan, M. M. A., Ali, J., ... & Shahid, M. (2021). Lemongrass essential oil components with antimicrobial and anticancer activities. *Antioxidants*, *11*(1), 20.

[9] Klauser, A. L., Hirschfeld, M., Ritter, A., Rücker, G., Jäger, M., Gundarova, J., ... & Asberger, J. (2021). Anticarcinogenic effects of odorant substances citral, citrathal R and cyclovertal on breast cancer in vitro. *Breast Cancer: Targets and Therapy*, 659-673.

[10] Luo, M., Jiang, L. K., Huang, Y. X., Xiao, M., Li, B., & Zou, G. L. (2004). Effects of citral on Aspergillus flavus spores by quasi-elastic light scattering and multiplex microanalysis techniques. *Acta Biochimica et Biophysica Sinica*, *36*(4), 277-283.

[11] Luciano, W. A., Pimentel, T. C., Bezerril, F. F., Barão, C. E., Marcolino, V. A., Carvalho, R. D. S. F., ... & Magnani, M. (2023). Effect of citral nanoemulsion on the inactivation of Listeria monocytogenes and sensory properties of fresh-cut melon and papaya during storage. *International Journal of Food Microbiology*, *384*, 109959.

[12] Faheem, F., Liu, Z. W., Rabail, R., Haq, I. U., Gul, M., Bryła, M., ... & Aadil, R. M. (2022). Uncovering the industrial potentials of lemongrass essential oil as a food preservative: a review. *Antioxidants*, *11*(4), 720.

[13] Capitain, C. C., Zischka, M., Sirkeci, C., & Weller, P. (2023). Evaluation of IMS drift tube temperature on the peak shape of high boiling fragrance compounds towards allergen detection in complex cosmetic products and essential oils. *Talanta*, *257*, 124397.

[14] Syafri, S., Jaswir, I., Yusof, F., Rohman, A., & Hamidi, D. (2022). The use of GC-MS and FTIR spectroscopy coupled with multivariate analysis for the detection of red ginger oil adulteration. *Rasayan Journal of Chemistry*, *15*(4), 2231-6.

[15] Rauber, C. D. S., Guterres, S. S., & Schapoval, E. E. (2005). LC determination of citral in Cymbopogon citratus volatile oil. *Journal of Pharmaceutical and Biomedical Analysis*, *37*(3), 597-601.

[16] Banerjee, M. B., Chowdhury, S. R., Roy, R. B., Tudu, B., Ghosh, M., Pramanik, P., & Bandyopadhyay, R. (2020). Development of a low-cost portable gas sensing system based on molecularly imprinted quartz crystal microbalance sensor for detection of eugenol in clove oil. *IEEE Transactions on Instrumentation and Measurement*, *70*, 1-10.

[17] Banerjee, M. B., Pradhan, S., Roy, R. B., Tudu, B., Das, D. K., Bandyopadhyay, R., & Pramanik, P. (2018). Detection of benzene and volatile aromatic compounds by molecularly imprinted polymer-coated quartz crystal microbalance sensor. *IEEE Sensors Journal*, *19*(3), 885-892.

[18] Banerjee, M. B., Tudu, B., Ghosh, M., Bandyopadhyay, R., Pramanik, P., & Roy, R. B. (2022). Detection of Carvacrol Content in Oregano Essential Oil by Molecularly Imprinted Polymer Coated Quartz Crystal Microbalance Sensor. *IEEE Sensors Journal*, *22*(8), 7692-7699.

[19] Gangopadhyay, D., Nag, S., Dasgupta, S., Banerjee, M.B., Tudu, B., Das, D., Pramanik, P., Bandyopadhyay, R. and Roy, R.B., 2023. A Simple and Efficient Formaldehyde Detection Technique Using Poly Ethylene Glycol Modified Quartz Crystal Microbalance Sensor. *Nano LIFE*, *13*(02), 2350005.

[20] Sauerbrey, G. J. Z. P. (1959). The use of quartz oscillators for weighing thin layers and for microweighing. *Z. Fur. Phys.*, *155*, 206-222.

[21] Kundu, S., Gangopadhyay, D., Moulick, M., Bhattacharyya Banerjee, M., & Roy, R. B. (2023). Discrimination of different Citronella essential oil samples depending on citronellal using QCM based Sensor. *American Journal of Electronics & Communication*, *4*(1), 25-28.

[22] Marques, A. M., Lima, C. H., Alviano, D. S., Esteves, R. L., & Kaplan, M. A. C. (2013). Traditional use, chemical composition and antimicrobial activity of Pectis brevipedunculata essential oil: A correlated lemongrass species in Brazil. *Emirates Journal of Food and Agriculture*, 798-808.

[23] Majewska, E., Kozlowska, M., Gruszczynska-Sekowska, E., Kowalska, D., & Tarnowska, K. (2019). Lemongrass (Cymbopogon citratus) essential oil: extraction, composition, bioactivity and uses for food preservation-a review. *Polish Journal of Food and Nutrition Sciences*, *69*(4).

[24] Barbosa, L. C. A., Pereira, U. A., Martinazzo, A. P., Maltha, C. R. Á., Teixeira, R. R., & Melo, E. D. C. (2008). Evaluation of the chemical composition of Brazilian commercial Cymbopogon citratus (DC) Stapf samples. *Molecules*, *13*(8), 1864-1874.

[25] Nag, S., Das, D., Naskar, H., Tudu, B., Bandyopadhyay, R., & Roy, R. B. (2023). A Novel Molecular Imprinted Polymethacrylic Acid Decorated Graphite Electrochemical Sensor for Analyzing Metanil Yellow Adulteration in Food. *IEEE Sensors Journal*.

[26] Nandiyanto, A. B. D., Oktiani, R., & Ragadhita, R. (2019). How to read and interpret FTIR spectroscope of organic material. *Indonesian Journal of Science and Technology*, *4*(1), 97-1

American Journal of Electronics & Communication

Shouvik Ghosh et. al., American Journal of Electronics & Communication, Vol. IV (3), 6-10

Lung Cancer Prediction Using Supervised Machine Learning

Shouvik Ghosh[1], Satavisha Sur[2] and Debanjana Ghosh[3]

Department of Electronics and Communication
University of Engineering and Management, Kolkata

[1]ghoshshouvik500@gmail.com
[2]satavishasur7@gmail.com
[3]debanjana.ghosh@uem.edu.in

Abstract: 'Cancer' in today's generation has become a prime factor of concern as because if we compare our past decade with the present, the statistical studies say the death rate has increased by 21% since 1990. So here we have brought up a model which detects lung cancer with high precise accuracy. 'Lung Cancer' are cells that develop in the lungs, due to certain exterior factors. As cancer cells grow rapidly, symptoms are caught at the last stage at maximum situations. So, to put this as our top priority we have presented a Lung Cancer detection model using classification techniques such as (KNN Algorithm, Decision Tree and Confusion Matrix). The ultimate objective of this paper is the early diagnosis of 'Lung Cancer', in order to increase the chances of survival.

Keywords - Lung Cancer, Classification Algorithm, KNN Algorithm, Decision Tree, diagnosis.

I. Introduction

Lung Cancer has taken a topmost position in the rankings of cancer. Too much consumption of Tobacco and Intake of regular Alcohol are some of the common reasons which may lead to lung cancer. The main reason behind this is the 'lack of awareness '. The lack of Knowledge is the major drawback specially in a country called India. The key to improve the survival rate is early detection using Machine Learning Techniques and if we can make the diagnosis process more efficient and effective for radiologists by using this, then it will be a key step towards the goal of improved early detection. Machine Learning takes AI to the next level as it enables intelligent learning to occur within the component based on previous work it did or extrapolations made from data. In the year 2018,

U.S.A brand-new cancer cells instances of 1,682,210 and fatalities of 896,690. As a result of the impact of the Lung Cancer cells or otherwise acknowledgement of lung cancer cells at the very early action the survival price is a lot less than various other cancer cells. The dataset which we used for training our model is taken from Boston UCI Repository ML Lung – Cancer Dataset.

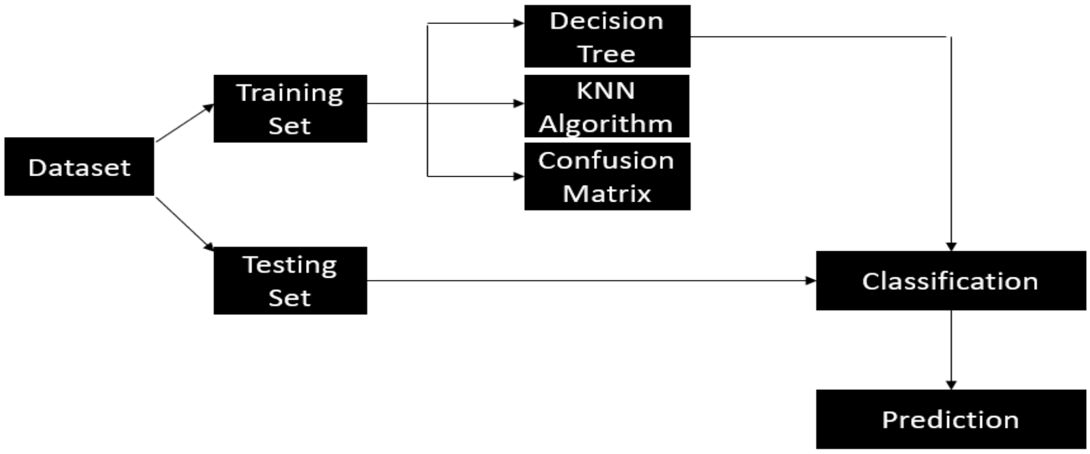
II. Literature Survey

Machine learning helps learning from previous data or work and can be used to train a model to predict diseases such as lung cancer by training the model with sets of previous data about lung cancer. A short and precise description about different research papers on lung cancer detection using ML are given below.

[1] This paper deals with reduction of risk of lung cancer by predicting the cancer early. Classification algorithms such as Naïve Bayes, SVM, Decision tree and Logistic Regression have been used for the prediction of lung cancer. A k-fold cross validation technique has been used for examining these classification algorithms. [2] This paper deals with the development of an ML model for prediction of a disease based on the symptoms of the patient. Decision tree classifier is used in this model to detect a disease by receiving the symptom data of the patient. Additionally, data from the patient's EHR is gathered in order to use NLTK to summarize the prescription and test results. [3] The authors of this paper have designed a system that can efficiently discover the rules to predict the risk of heart disease of the patients based on the parameters given about their health. The performance of the system is then evaluated by using classification accuracy to predict heart disease risk level more accurately. [4] The author of this paper states that the healthcare industry gathers a large amount of heart disease data and discovers hidden information for effective decision making for the prediction of heart diseases. Data mining techniques are used for analyzing data and for identifying relationships. This paper explores the working of various decision tree algorithms in classifying and predicting the disease. [5] This paper deals with the development of an Alzheimer disease prediction model which would be used to assist medical professionals in predicting the status of the disease when the medical data about the patients are provided. This model uses the decision tree algorithm on the sample data that has five important attributes namely gender, age, genetic causes, brain injury and vascular disease. [6] In this paper the author talks about the comparison of the reliability of association rule and decision tree

for disease prediction. The paper says experiments have shown that decision trees can find simple rules. Their reliability is somewhat low and refers to a small number of patients, but by comparison the association is reliable and often refer to larger set of patients. [7] This paper deals with the investigation of the accuracy level of various ML algorithms that deal with the prediction of lung cancer. The accuracy level of different models is evaluated, and the limitations and drawbacks are listed out. The author talks about the need for the development of a better model for prediction because none of the accuracy of the previous models have reached near 100%. [8] This paper deals with the development of a heart disease prediction model by using J48 decision tree for classifying heart diseases based on the clinical features against unpruned, pruned and pruned with reduced error pruning approach, which gives better accuracy. [9] This paper discusses the development of a model that can detect mental health problems in a wide range of patients. The mental health monitoring system will be able to measure stress based on various physical parameters such as heart rate, Spo2, body temperature and pressure, and will also have GPS sensors to track and rescue distressed patients in an emergency.

III. Block Diagram



This is the ultimate block diagram which shows the workflow of our Machine Learning Model.

- Initially, the dataset has been taken along with performing Data-Preprocessing Techniques of removal of outliers and Data-Cleaning.
- The Dataset is further divided into Training and Testing datasets.
- Using the Decision- Tree, KNN Algorithm along with their Confusion Matrix, the training data is fed into the two classifiers and the model is trained.
- The model is therefore evaluated with the testing data.
- Finally, the prediction results are taken.

IV. Classification Algorithms

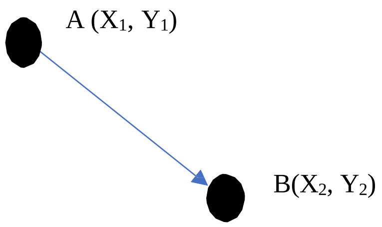
A. Decision Tree:

Decision Tree is a classification algorithm which is of three types, mainly Binary, Multi class and Multi Label. We have used Binary classification of '1'and '0'. Where '1' -> The person has a high probability of suffering from Lung Cancer. And '0' says that the person has low chances of Lung Cancer.

The root node is the node which the decision tree classifier wants to predict. They are calculated by two methods: 1. Gini Indexing 2. IG [Information Gain] & Entropy. The root node is the node with the highest IG. The following comes the Leaf node, which has no further classifications. The classifier has decided whether it's a yes or a no. The leaf node has no further branches.

B. KNN Algorithm:

KNN stands for K -Nearest Neighbor. This algorithm is used to predict an unknown data point belonging to a specific class. It is calculated by the Euclidean distance between any data point of any class and the unknown data point. The working principle goes as follows: The unknown data point is placed on the graph. Now we take randomly 5 – 6 datapoints close-by as the nearest neighbors of the unknown data point. Now in order to calculate the radius we find the *Euclidean Distance* (default distance measuring unit in KNN Algorithm). We calculate it by the following methodology:



Therefore, the Euclidean Distance between the two points is:

$$\sqrt{(X1 - X2)^2 - (Y1 - Y2)^2}$$

Now repeating the steps for other points and now, the shortest distance of all points will determine which class does the unknown point determine.

V. Workflow diagram

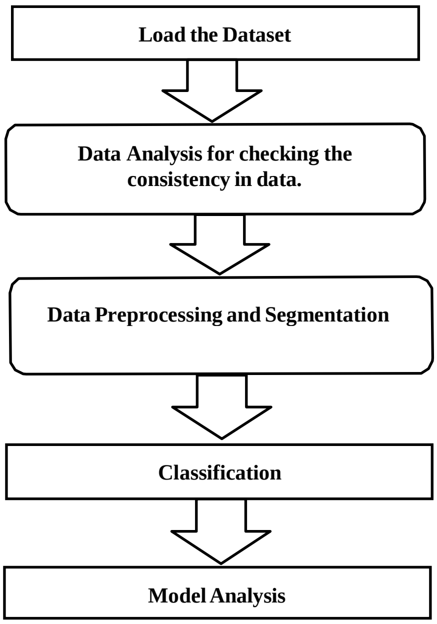


Fig. 1

VI. Model Results

The below graphs show the resultant output after the model gets trained with all the classifier.

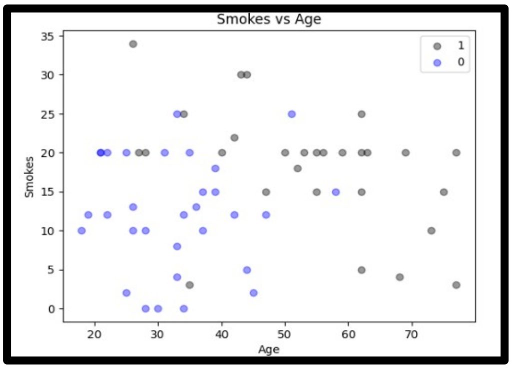


Fig. 2

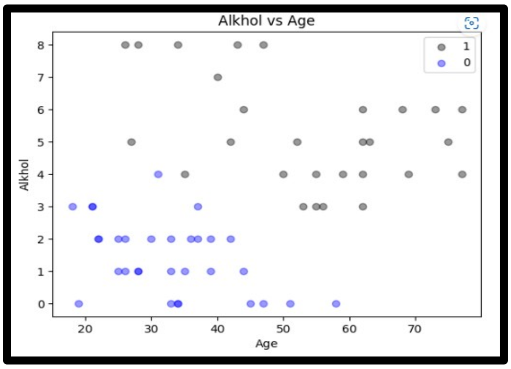


Fig. 3

The graph in Fig. shows the smokes vs age graph which tells us the chances of having Lung Cancer if an individual smokes as per the quantity of cigarettes per day according to the age. The parameters are; : The person has low chances of Lung Cancer, whereas : The person has high chances of Lung Cancer. The graph in Fig. points out the probability of Lung Cancer of individuals according to the Alchohol consumption quantity. The parameters are; : The person has low chances of Lung Cancer, whereas : The person has high chances of Lung Cancer.

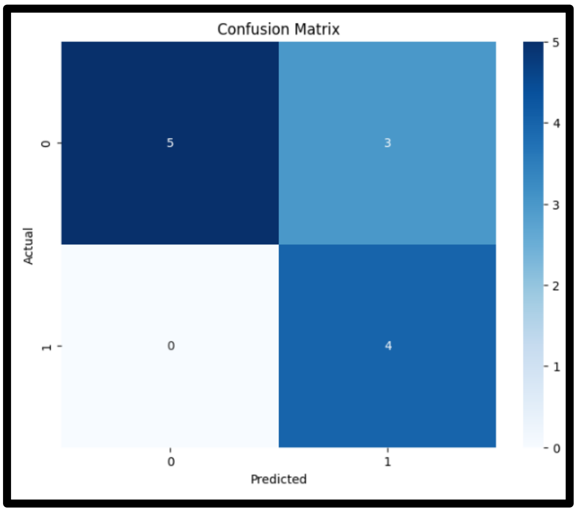


Fig. 4 Confusion Matrix for Decision Tree Classifier

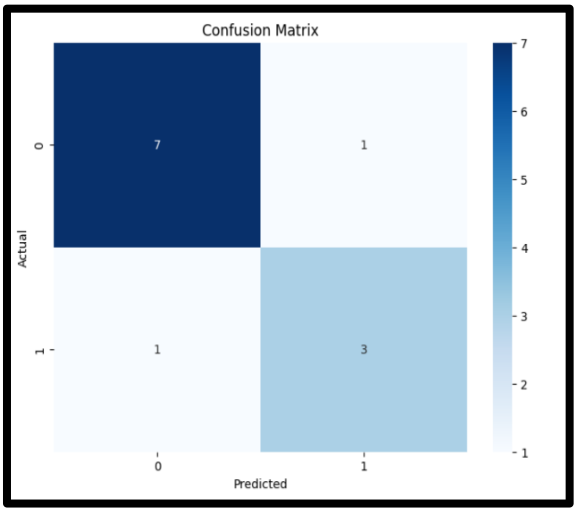


Fig. 5 Confusion Matrix for KNN Algorithm

Classifier	Accuracy
Decision Tree	92.03%
KNN	83.34%

Table 1 : Comparison of Accuracy

Classifier	Sense	Spec	Pres
Decision Tree	1.0	0.625	0.571
KNN	0.75	0.875	0.75

Table 2 : Comparison of Sensitivity, Specificity, Precision

VII. Problem Faced

Although our model, which has been trained using an open source dataset can predict lung cancer with an accuracy above 80%, availability of hospital test dataset of real patients would have improved the performance and accuracy of our model.

VIII. Future Scope

We can implement deep learning for image classification of CT scan, MRI and Ultrasound test of patients. We will use original data of the patients for training our ML model. We can train our ML model to detect other diseases apart from lung cancer. We can create a website for easier approach by the end users.

IX. Conclusion

We have finally succeeded in creating a ML Model which would predict precisely whether a person has Lung Cancer or not. Earlier back in history when there were no modern techniques and AI, ML, DL was not in action, it was difficult for doctors to predict manually, and even today early symptoms of cancer is not predictable. So with the modern techniques and application of AI, ML and DL we have created a model with a goal of early diagnosis of Lung Cancer.

X. References

[1] “A Comparative Study of Lung Cancer Detection using Machine Learning Algorithms”, Department of Computer Science and Engineering, Amrita Vishwa Vidyapeetham, Amrita Puri, India, IEEE 2018.

[2] “Symptoms Based Disease Prediction Using Decision Tree and Electronic Health Record Analysis”, European Journal of Molecular & Clinical Medicine, ISSN 2515-8260 Volume 7, Issue 4, 2020.

[3] “Efficient heart disease prediction system using decision tree”, International Conference on Computing, Communication and Automation (ICCCA 2015).

[4] “Heart Disease Prediction Using Classification with Different Decision Tree Techniques”, International Journal of Engineering Research and General Science Volume 2, Issue 6, October-November 2014.

[5] “Using decision tree classification to assist in the prediction of Alzheimer’s disease”, 2014 6th International Conference on CSIT.

[6] “Comparing Association Rules and Decision Trees for Disease Prediction”, Carlos Ordonez, University of Houston, Houston, TX, USA-November 2006.

[7] “An extensive review on lung cancer detection using machine learning techniques”, Article in Journal Critical Reviews - May 2020.

[8] “A heart disease prediction model using decision tree”, IOSR Journal of Computer Engineering (IOSR- JCE), e-ISSN: 2278-0661, p- ISSN: 2278-8727Volume 12, Issue 6 (Jul. - Aug. 2013), PP 83-86.

[9] “IoT based smart system to detect mental health emergencies: A proposed model”, American Journal of Science and Engineering volume-2, Issue-4 - March 2022.

American Journal of Electronics & Communication

Soumyadipta Mukherjee et. al., American Journal of Electronics & Communication, Vol. IV (3), 11-15

IOT BASED FOOD SPOILAGE DETECTION SYSTEM

Soumyadipta Mukherjee
Electronics And Communication Engineering
University Of Engineering & Management
Kolkata, India
soumyadiptamukherjee2004@gmail.com

Swastik De
Electronics And Communication Engineering
University Of Engineering & Management
Kolkata, India
deyswastik27@gmail.com

Swapneel Roy
Electronics And Communication Engineering
University Of Engineering & Management
Kolkata, India
swapneelroy6025@gmail.com

Swastik Dev Chaklader
Electronics And Communication Engineering
University Of Engineering & Management
Kolkata, India
swastikdev04@gmail.com

Subham Maity
Electronics And Communication Engineering
University Of Engineering & Management
Kolkata, India
subhammaity1129@gmail.com

ABSTRACT :-

About 351,000 people die of food poisoning globally every year. In some countries, majority of people struggle on daily basis for food, due to preservation of foods and use of chemicals to artificially increase the time span of food causes people illness. Food contamination is more dangerous because very often food does not look bad even though severely infected, it may appear quite normal. The presence of highly dangerous toxins and bacterial spores is often not detected until after an outbreak of food poisoning, laboratory examination uncovers the infecting agent. It is necessary to develop a system that can help people to identify the freshness of food or quality of food items. Based on the research, the hypothesis is that, as food decays, they emit certain gases which can be detected by Arduino based sensors, and the levels of these gases will vary depending on the extent of the decay. The measurement of parameters like alcohol, methane gas level in food items is necessary to determine freshness and quality of food. It serves the purpose of consumer health protection by maintaining the required standard to preserve the quality of food. The status of the food is not fresh all the time.

The proposed system will help people to identify the freshness of food or the quality of food items. Our purpose is that the system may give better quality and freshness in food. General awareness of nutrients in food must be known by the consumer. Food poisoning has been the source of innumerable diseases that has a bad effect on health. To avoid illness, we use sensors to determine the freshness of household food items like fruits which can reduce food poisoning. Project captures activities performed by IOT based food spoilage detection system. The food we consume can affect in any form of contamination that may occur due to storage or chemical reaction within the food. There are several viruses and bacteria that causes food contamination and leads to numerous foodborne diseases, for example Noro virus a very contagious virus caused by contaminated food or water. Most of the people die of food poisoning globally every year. It is essential to develop a system that can help people to identify the freshness of food or quality of food items. Our proposed system may give the good quality (freshness) management in food.[1]

KEYWORDS :-

FSD SYSTEM, FOOD POISONING, ARDUINO SENSORS, METHANE, HEALTH.

[I] INTRODUCTION :-

The food we consume provides nourishment and gives energy to our body, it gives us the ability to do daily activities and help improves our health in direct as well as indirect ways. A healthy and fresh diet is the most important way to keep ourselves fit. The food items kept at room temperature undergo rapid bacterial growth and chemical changes in food. Taking unhealthy food leads to bad health and can cause different food borne diseases. Indian scenario is even worse with foodborne illnesses causing outbreaks in almost every part of the country. Though most foodborne diseases are sporadic and often not reported in India, a nationwide study carried out recently reported an alarming prevalence of 13.2% at the household level. The scientific reports on the outbreak of foodborne diseases in India for the past 29 years indicated that a total of 37 outbreaks involving 3485 persons have been affected due to food poisoning. Today, in most of the hostel mess and government schools' kitchen everybody is getting affected by the food they consume. Fruits like banana and other food items used in daily life, as all of them do not offer quality since their moisture, harmful gases vary from time to time. To ensure food safety it should be monitored at every stage of the supply chain. When foods start decaying it produces some gases like ethanol, methane in it. These gases increase with time. The purpose of this system is to detect early food spoilage before signs are visible. Food safety and hygiene is a major concern in order to prevent the food wastage. The Quality of the food needs to be monitored and it must be prevented from rotting and decaying. Therefore, it is useful to deploy quality monitoring devices at food stores. These quality monitoring devices keep a watch on the environmental factor that cause or pace up decay of the food.[2][3]

MATERIALS & METHODOLOGY :-

[II] MATERIALS :-

1) ARDUINO UNO R3 :-

• The Arduino Uno R3 is a microcontroller board based on a removable, dual-inline package (DIP) ATmega328 AVR microcontroller (as shown in FIG 1).

• It has 20 digital input/output pins (of which 6 can be used as PWM outputs and 6 can be used as analog inputs).

• Programs can be loaded on to it from the easy-to-use Arduino computer program.

Arduino Uno R3 Specifications-

The Arduino Uno R3 board includes the following specifications.

• It is an ATmega328P based Microcontroller.
• The Operating Voltage of the Arduino is 5V.
• The recommended input voltage ranges from 7V to 12V.
• The I/p voltage (limit) is 6V to 20V.
• Digital input and output pins-14.
• Digital input & output pins (PWM)-6.
• Analog i/p pins are 6.
• DC Current for each I/O Pin is 20 mA.
• DC Current used for 3.3V Pin is 50 mA.
• Flash Memory -32 KB, and 0.5 KB memory is used by the boot loader.
• SRAM is 2 KB.
• EEPROM is 1 KB.
• The speed of the CLK is 16 MHz.
• In Built LED.
• Length and width of the Arduino are 68.6 mm X 53.4 mm.
• The weight of the Arduino board is 25 g.

3) WIFI ESP8266 SENSOR :-

• The ESP8266 is a low-cost Wi-Fi microchip, with a full TCP/IP stack and microcontroller capability (as shown in FIG 1).

• This small module allows microcontrollers to connect to a Wi-Fi network and make simple TCP/IP connections.

5) BUZZER :-

A Piezo buzzer is an electric device used to produce a tone. These lightweight and simply constructed buzzers are inexpensive yet reliable and come in a range of sizes and frequencies to meet the needs of nearly any application (as shown in FIG 1).

7) USB :-

The USB port in the Arduino board is used to connect the board to the computer using the USB cable. The cable acts as a serial port and as the power supply to interface the board (as shown in FIG 1).

2) MQ4 SENSOR :-

• This methane gas sensor detects the concentration of methane gas in the air and outputs its reading as an analogue voltage. (as shown in FIG 1).

• The concentration sensing range of 300 ppm to 10,000 ppm is suitable for leak detection.

• . The sensor can operate at temperatures from -10 to 50°C and consumes less than 150 mA at 5 V.

4) BREADBOARD :-

• A Breadboard is a widely used tool to design and test circuit. (as shown in FIG 1).

• We do not need to solder wires and components to make a circuit while using a bread board.

• It is easier to mount components & reuse them.

• Since, components are not soldered we can change our circuit design at any point without any hassle. Other components we have used are connecting wires, green and red LEDs, power supply, etc.

6) POWER SUPPLY :-

The Arduino can be powered via the USB connection or with an external power supply. External power can come either from an AC- to- DC adapter (wall-wart) or battery. The circuit operates on 5V DC. We can also provide power supply through laptop or PC connected through USB or through battery (as shown in FIG 1).

FIGURE 1:- ARDUINO UNO,MQ4 SENSOR,WIFI ESP8266 SENSOR,BUZZER,BREADBOARD, POWER SUPPLY,USB CABLE.

[III] METHODOLOGY :-

1. IMPLEMENTATION :-

This Arduino based FSD system should be installed in food store. Once it is properly installed and powered on, it connects with the internet via the Wi-Fi module and starts reading data from the interfaced sensor –MQ4 Sensor. The MQ4 sensor detects the emission of methane types of gases. If the food/fruits get spoiled, they emit the methane type of gases. The MQ4 sensor detects the concentration of such gases and outputs an analog voltage proportional to the concentration of the gas. The analog output is passed to the analog pin of the Arduino which has an inbuilt ADC that converts the analog to a digital value. The Arduino collects data from the sensor and converts the values to the strings. The sensor data wrapped as proper strings. Wi-Fi module connected to the Arduino uploads the data to Server where the processing of data takes place. The values are compared to the threshold values which gives the result that whether the food is fresh or not with a predefined algorithm. The values are sent back to the Arduino. Arduino displays the output on Blynk app dashboard "Food spoiled" depending upon the food freshness level (i.e. depending upon methane content). It also display the range of methane content in ppm.[4]

2. PROCESS :-

1. A customer needs to download 'Space Wix' app there he/she can request to signup/login with user credentials. Once owner logins, he should be able to see the dashboard where he/she will have to create project with any title say 'FSD SYSTEM'. There it is required to set hardware component through which sensor data is going to be sent to the server. Also the connection type is to be mentioned say Wi-Fi (or Ethernet, USB, etc..).
2. Store manager will approve the login request. On approval, an approval email would be sent to the customer's email id. Email id of the customer is a valid user. He will be provided with a auth token which is to be used for programming for NodeMCU to connect to the blynk server.
3. He will have to specify the ssid and the password of the Wi-Fi in the required program to connect to FSD System to the internet. Manager should be able to see following reports
•Methane Range in the fruits as sensed by the sensor.
•"Food Spoiled" message when it is detected range above 250 ppm.
3. A soon as the manager gets the text on the Blynk app dashboard, he is expected to take actions regarding the spoiled food and also consuming those fruits which are at the stage of spoilage.
4. It requires hardware PC/laptop with 2 GB hard-disk and 256 MB RAM or an android phone
and it can be used to power the Arduino.[5]

3. FSD MODEL :-

FSD System is lit with a green LED until it comes in contact with the spoiled food emitting methane or more precisely fruits. As soon as the sensor senses any spoiled fruit it triggers a buzzer and a red LED is lit. The range or value of methane measured in ppm by the sensor is displayed on the dashboard of 'Blynk app'. Also, with the help of ESP8266 Wi-Fi module the specific range can be seen through any IOT project-based websites like Thingspeak.com or any applications like Blynk or any other cloud which can be used as a IOT portal.
There we can see the range of methane produced by fruits which are spoiled. Normally the fresh fruits have methane content below 250 ppm, if it goes above this then it is an indication of fruit spoilage. So, with the help of these IOT project-based applications a message of "Food Spoiled" will be printed on the screen of 'Blynk app'.[6]

4. BLOCK DIAGRAM :-

Arduino needs to be given a power supply it can given through may sources like barrel adapter, the USB connector by connecting it to a PC/laptop, batteries greater than 5V supply, using battery shield etc. We used USB connector from Arduino to PC. Different components required are MQ4 Methane sensor, ESP8266 Wi-Fi wireless module, green led, red led, and few other components include bread board, connectors, resistors, batteries for other power sources required, buzzer etc. All these are connected to the Arduino with the help of breadboard. A network can be established through a mobile hotspot which is sensed by ESP8266 Wi-Fi module and our Arduino can share the data sensed by the sensors connected to it to the IOT portal or any other cloud where user could know the range of methane in ppm produced by the spoiled food. When the food spoilage is sensed by MQ4 methane sensor the buzzer is triggered and a red LED is lit. So user could know about the food spoilage. Also a mail is generated by the IOT based applications in our case (Blynk app) and is sent to the user of FSD system. (as shown in FIG 2).

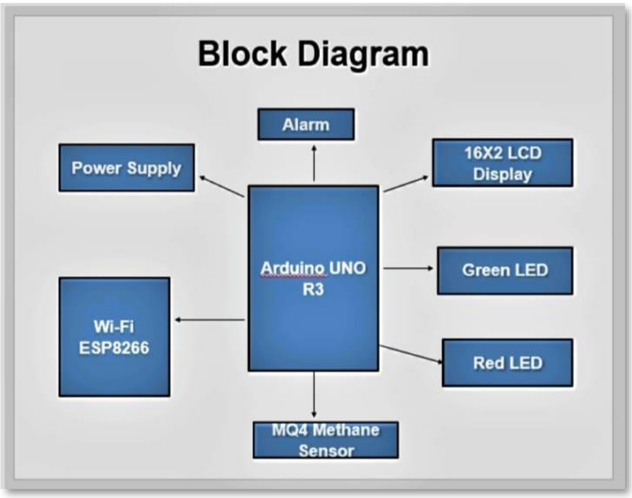


FIGURE 2:- BLOCK DIAGRAM OF FSD SYSTEM

[IV] RESULT :-

• Quality is monitored constantly by sensors and readings are displayed on screen.

• When abnormal readings are detected in any readings i.e., MQ4 sensor, it displays the food spoiling message on the LED screen.(as shown in Fig 3)

• It also displays a message of "Food Spoilage" on the Blynk application dashboard. .(as shown in Fig 4)

• The data over Dashboard gets updated every seconds.

• User will also be able to see the values on serial monitor of Arduino IDE and the specific graph on the serial plotter of Arduino IDE.

[V] FUTURE SCOPE:-

• Using high precision sensors to increase the area of sensing.
• We can modify the project by using two or more sensors which will display dual parameters on the screen.
• We can modify this project and use for big warehouses and go downs where manually checking of eatables is not possible.
• This FSD system can also be used by anyone who owns refrigerator or may not having refrigerator as sometimes person may forget to consume any food item before its expiry date so it gets spoiled and is overlooked so it can be useful to detect freshness of each item present in the fridge or else at home. In that also different sensor can be used.

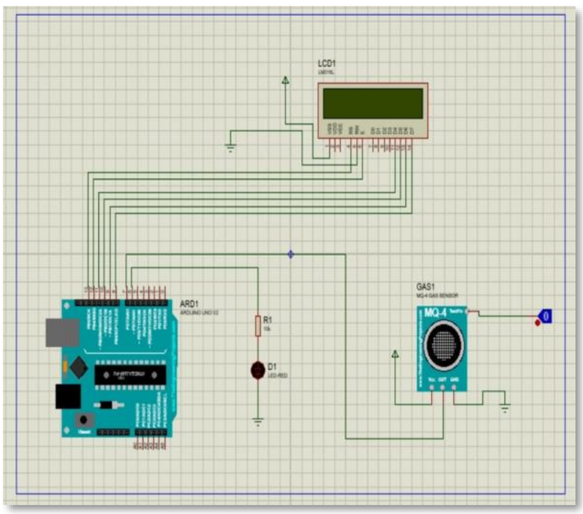


FIGURE 3 -CIRCUIT DIAGRAM OF FSD SYSTEM.

FIGURE 4- BLYNK IOT APP

[VI] CONCLUSION :-

- Food poisoning has been the source of innumerable diseases, to reduce and avoid illness we use sensors to determine the freshness of household food items like fruits.

- The Arduino sensors can detect gas emissions using sensors to detect the presence of these values among foods can help detect food spoilage early and prevent the consumption of spoiled food.

- These techniques can be further developed to include other types of gas sensors and foods to increase the sensitivity of such detection methods.

- This system consists of a hardware device i.e. Mq4 Methane Sensor which checks the quality and freshness of food.

[VII] REFERENCES :-

1. e Fresh – A Device to Detect Food Freshness : International Journal of Soft Computing
and Engineering (IJSCE) ISSN: 2231-2307, Volume-8 Issue-3, September 2018.

2. "FOOD QUALITY MONITORING SYSTEM BY USING ARDUINO"B.Ravi Chander
, P.A.Lovina ,G.Shiva Kumari Assistant Professors, Dept. of ECE, St. Martin's
Engineering college, Dhulapally(v), kompally,Secunderabad 500100 Telangana state,
India. Journal of Engineering Sciences(JES) Vol 11, Issue 4 , April/ 2020.

3. "An Efficient System to Detect Freshness and Quality of Food" Suruchi Parmar, Tejaswini
Manke, Neha Badhan, Prasad Borase, Prof. N.S. Ujgare Student, Dept. Of Information
Technology, KBT College of Engineering, Maharashtra, India Assistant Professor Dept. of
Information Technology, KBT College of Engineering, Maharashtra, India. International
Research Journal of Engineering and Technology (IRJET),Volume 7.

4. "An Intelligent IoT-Based Food Quality Monitoring Approach Using Low-Cost Sensors"
Alexandru Popa , Mihaela Hnatiuc , Mirel Paun , Oana Geman , D. Jude Hemanth , Daniel
Dorcea , Le Hoang Son and Simona Ghita .Symmery EISSN 2073-8994, published by
MDPI.

5. "Arduino Based Smart IoT Food Quality Monitoring System", March 21,2018.By Hai
Prasaath K. Engineers Garage –An EE world online resource.

6. Food Spoilage: Microorganisms and their prevention by Seema Rawat .Pelagia Research
Library-Asian Journal of Plant and Science and Research ,2015.

American Journal of Electronics & Communication
Shaik Nehar et. al., American Journal of Electronics & Communication, Vol. IV (3), 16-23

Automatic Number Plate Recognition

Shaik Nehar
Department of AI&DS ,Bachelor of Scholars
Vasireddy venkatadri institute of technology
Nambur,guntur,522007.
neharimran@gmail.com

Sanagala Teja
Department of AI&DS ,Bachelor of Scholars
Vasireddy venkatadri institute of technology
Nambur,guntur,522007.
sanagalateja12@gmail.com

Lohith vattikuti
Department of AI&DS ,Bachelor of Scholars
Vasireddy venkatadri institute of technology
Nambur,guntur,522007.
lohithvchowdary@gmail.com

Sai vignesh chintala
Department of AI&DS ,Bachelor of Scholars
Vasireddy venkatadri institute of technology
Nambur,guntur,522007.
Ch.vignesh2003@gmail.com

SrinivasaRao Tummalapalli
Department of AI&DS ,Bachelor of Scholars
Vasireddy venkatadri institute of technology
Nambur,guntur,522007.
srinut422@gmail.com

Mahendra Eda
Department of AI&DS ,Bachelor of Scholars
Vasireddy venkatadri institute of technology
Nambur,guntur,522007.
mahindramahi08@gmail.com

Abstract:-** This innovative and comprehensive approach harnesses the combined power of YOLOv8 and EasyOCR technologies for Automatic Number Plate Recognition (ANPR). The primary objective is to extract valuable data from vehicle images, even when they are blurred or distorted, and utilize this data for further analysis using machine learning models.The cornerstone of this approach is the integration of two cutting-edge technologies: You Only Look Once (YOLO) V8 for Region of Interest (ROI) detection and EasyOCR for optical character recognition. The workflow begins with the utilization of YOLOv8, which excels in identifying and correcting distorted license plates within a single image. Its initial task is to pinpoint the Region of Interest (ROI). Once the ROI is identified, a series of pre-processing steps are employed to enhance the image quality before feeding it into the EasyOCR model for character recognition.Several significant advantages distinguish this approach. Firstly, it possesses the capability to deblur images, enabling accurate data extraction even from blurred or challenging images. Secondly, it synergizes the strengths of YOLOv8 for precise ROI detection and EasyOCR for accurate character recognition, resulting in a robust and dependable ANPR system. Lastly, the system is optimized for real-time processing, rendering it suitable for applications requiring swift and efficient vehicle monitoring.The key innovation lies in the ability to extend its functionality to video data, allowing for the detection of number plates in dynamic settings. It not only detects license plates but also provides an annotated video with comprehensive license plate details. This holistic approach facilitates a more complete understanding of vehicular movements and activities.By harnessing the capabilities of YOLOv8 and EasyOCR technologies, this approach delivers a comprehensive and sophisticated solution for Automatic Number Plate Recognition. It enhances accuracy, efficiency, and the ability to handle challenging scenarios, such as blurred images and dynamic video feeds. This innovative system serves as a valuable tool for promoting safe, secure, and modern transportation systems.

***keywords:** Yolov8,EasyOCR,Region of Interest, Character Recognition*

I. INTRODUCTION

Automatic Number Plate Recognition (ANPR) is a technology that optimizes the movement of automobiles over transport networks. ANPR involves acquiring and analyzing images from traffic surveillance cameras, and it has gained momentum in recent years due to the advancements in neural networks and deep learning[2]. ANPR can be applied to many areas, like traffic law enforcement, automatic toll tax collection, car parking systems, and automatic vehicle parking systems[6].

The steps involved in ANPR are image acquisition, preprocessing of the image, finding the region of interest (ROI), segmentation, and optical character recognition. The initial phase of ANPR is image acquisition, where input images can be extracted from traffic surveillance videos. The second step is finding the Region of Interest, which in this case is a license plate present in the image. Edge detection is the most common method to use for number plate detection, and more techniques are used for plate detection[2]. In the next stage, after the detection of the plate, segmentation is done to identify the regions where alphanumeric characters are present. The final step is to recognize the segmented region as alphanumeric characters.

To improve the accuracy and efficiency of ANPR, researchers have proposed a novel approach that combines the power of YOLOv8 and EasyOCR technologies[1].While EasyOCR can identify the characters on a license plate that has been identified, the YOLOv8 model can detect and correct numerous distorted license plates in a single image. The suggested method has a number of benefits, including the capacity to handle blurry photos, which makes it an important tool for contemporary, secure, and safe transportation systems[4].

The ANPR systems placed along the roadways can be used to detect stolen automobiles in an effective manner. This paper presents a recognition method that uses the YOLO algorithm for Automatic Number Plate Recognition

(ANPR)[1].A Convolutional Neural Network (CNN) was suggested in another study to be capable of identifying and correcting several deformed license plates in a single image, which would then be fed into an optical character recognition (OCR) approach to get the desired outcome[2]. The Plate Recognizer team has created Automatic License Plate Recognition (ALPR) software that is location-specific and functional in any setting.

The final segment is as follows: Section II provides a summary of the literature review of the previous study. The techniques employed for the planned study are described in Section III. The outcomes of the chosen strategy are explained in Section IV. The suggested work is concluded in Section V, which also makes mention of future work.

II. Related Work

Finding and identifying license plates in photographs is the duty of ANPR[2-3]. Character segmentation, vehicle detection, license plate detection, and character recognition are the four subtasks that typically make up a sequential pipeline.We'll just call the culmination of the past two tasks optical character recognition for short.

License plate localization is an essential step in Automatic Number Plate Recognition (ANPR), and traditional methods based on a priori information are generally classified as color texture, shape regression, and edge detection[5]. However, these methods have limitations because they rely on manual feature extraction, which is not well-suited to the diversity of images. Target identification techniques based on deep learning have advanced quickly in recent years, and the algorithms can be broadly split into two types.The first category generates a part of the candidate region by the algorithm, and then the candidate region is classified and positioned again. End-to-end detection techniques fall under the second group; these algorithms immediately obtain the target's coordinates and class probability. ANPR systems that use deep learning algorithms have shown high accuracy and efficiency. Ibtissam Slimani et al based their license plate detection on wavelet transform, followed by validation of potential regions using a CNN classifier. The YOLOv8 algorithm is an example of an end-to-end detection algorithm that is widely used in ANPR systems. It directly gets the location coordinates and class probability of the target, making it highly accurate and efficient[6].

Automatic Number Plate Recognition (ANPR) is a widely used computer vision application that involves finding and recognizing license plates in images. In the license plate recognition stage, traditional recognition algorithms segment the license plate characters one by one and then use optical character recognition (OCR) technology to recognize each character. However, this method has poor recognition efficiency[3-5]. Many ANPR systems can only achieve good recognition under specific conditions, such as good weather conditions, adequate lighting, fixed scenes, and facilities.It is still difficult to recognize license plates in complex situations due to problems including poor nighttime lighting, rain, snow, and covered or blurred license plates.In recent years, deep learning-based target detection methods have developed rapidly, and the algorithms are mainly divided into two categories. One category generates a part of the candidate region by the algorithm, and then the candidate region is classified and positioned again. End-to-end detection techniques fall under a different category and directly obtain the target's coordinates and class probability[6]. Our ANPR system uses an end-to-end method based on deep learning that optimizes the efficiency and accuracy of recognition. The system uses YOLOv8, a deep convolutional neural network, for license plate detection, and EasyOCR for character segmentation and recognition[3]. The combination of these two tools forms a sequential pipeline for ANPR, which consists of the four subtasks mentioned above. The OCR technology used in EasyOCR is robust and has very high accuracy, which is essential for accurate character recognition. Our ANPR system is capable of detecting license plates in unconstrained scenarios, which means that it can handle distorted text and high font variability[1].
According to a review of the literature, the following restrictions apply to the suggested algorithms:
1. Low image quality
2. Less Precision
3. Dim illumination and weak contrast
4. Increased Cost of Computation
5. A lack of regulations for automobile license plates
6. Characters that have been improperly segmented won't be recognized.

III. Methodology

My methodology involves the usage of YOLOv8 and EasyOCR for Automatic License Plate Recognition (ALPR). YOLOv8 is a deep convolutional neural network that is used for vehicle recognition and license plate detection, while EasyOCR is used for character segmentation and recognition. The combination of these two tools forms a sequential pipeline for ALPR.Fig. 1 shows the flow we followed.

Fig1: Flow diagram prepared for proposed methodology

A. *3.1 Vechile Recognition:*

Vehicle recognition is a crucial component of modern computer vision systems, with applications ranging from traffic management to surveillance and autonomous vehicles. In this context, the YOLOv8 algorithm plays a pivotal role as a powerful and efficient object detection framework[4]. Trained on the extensive COCO dataset, YOLOv8 exhibits the capability to detect a wide range of objects, including vehicles, in real-time video streams.

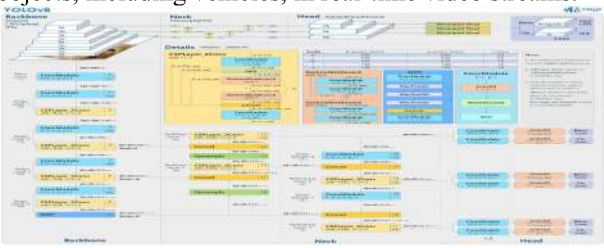


Fig:Yolov8 Architechture

The process of vehicle recognition begins with the input video stream, which is sequentially processed frame by frame[4-5]. Each frame is analyzed by the YOLOv8 model, which identifies potential vehicles within the image. The algorithm returns bounding boxes around these detected vehicles, accompanied by confidence scores that reflect the model's confidence in its predictions.

To ensure that only vehicles are considered for further analysis, the detected bounding boxes are filtered based on their associated class identifiers[4]. Vehicles typically have specific class identifiers, making it possible to distinguish them from other objects that may be present in the scene.

The resulting set of filtered bounding boxes, representing vehicles in the frame, forms the basis for subsequent analysis[5]. These bounding boxes are then passed to the license plate recognition system, which focuses on the regions of interest (ROI) containing the license plates of the detected vehicles. This two-step process not only identifies vehicles within the video stream but also paves the way for detailed analysis of license plate information, such as recognition and extraction[5].

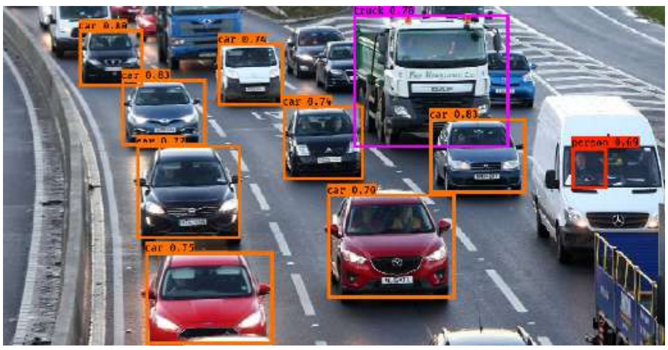


Fig:Vechile Recognition

B. *3.2Licence Plate Recognition:*

1) Preparing the dataset

The workflow begins with the installation of the Roboflow library, a tool that streamlines data management and preprocessing for machine learning projects, including LPR. The library facilitates the handling of image datasets, making it easier to prepare the data for training[6].

Within this context, a specific project and dataset are accessed using the Roboflow API. The chosen dataset likely contains a collection of images with labeled license plates, which serves as the training data for the LPR model. By leveraging this data, the system can learn to recognize and interpret license plates accurately3].

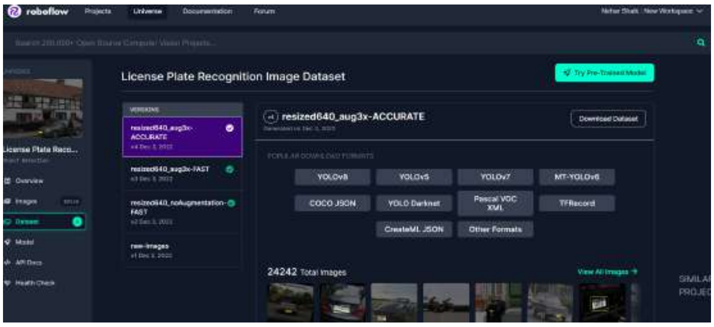


Fig:Data form Roboflow

2) Train the Model

In our project, we utilized YOLOv8 as our chosen model and conducted training over 120 epochs, completing the process in a notably reduced time of 0.981 hours. This runtime is significantly faster compared to the YOLOv5 model discussed in Figure , in collaboration with Google Colab. Additionally, in Figure of our study, we present the outcomes of YOLOv8's training on the training dataset, showcasing the recognized labels, as well as providing precision, recall, and mAP (mean Average Precision) values. This performance assessment highlights the effectiveness of our chosen YOLOv8 model in object detection tasks.

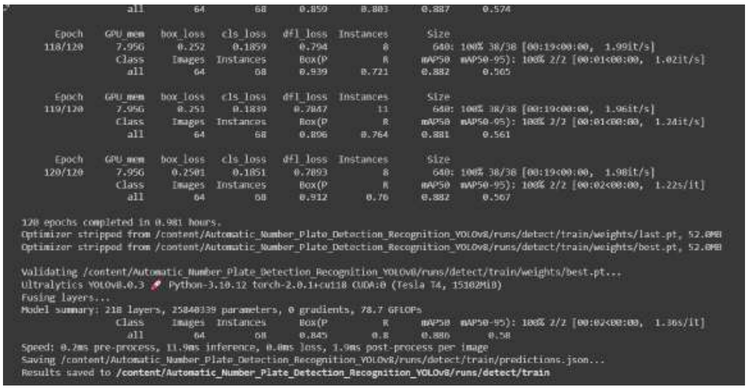


Fig:Yolov8 Model Training

3) Evaluating the model performance

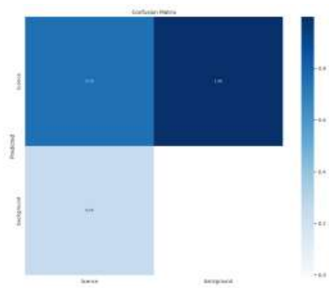


Fig:Confusion Matrix Of Model

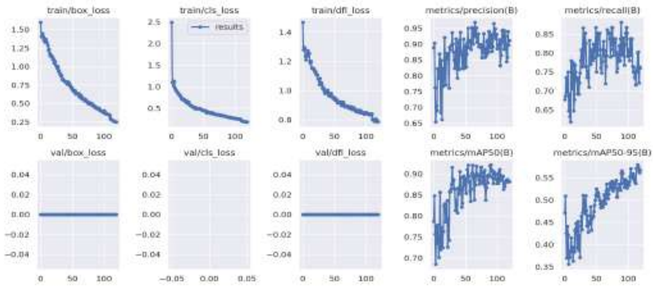


Fig:Metrix on object identification after testing the data

4) Checking the output generated from the model

Fig:Plates identified by Yolov8

It's important to note that training a license plate recognition model is a resource-intensive task that requires a substantial amount of labeled data, computational power, and time. The choice of architecture (YOLOv8 in this case) is significant, as it influences the model's performance in terms of accuracy and speed[5].

C. 3.3Licence Plate Image Enhancement

Within the realm of LPR, a crucial step involves the initial processing of license plate images to enable precise character identification[2]. The provided segment of the process emphasizes the significance of this preparatory phase, which entails transforming license plate images into grayscale and then applying thresholding[2-3].

Fig: Original Licence Plate

The conversion to grayscale simplifies the license plate image by eliminating color information, resulting in a single-channel image where pixel values represent varying degrees of brightness[2]. This simplification reduces the intricacy of the image data, streamlining subsequent processing steps to concentrate exclusively on luminance data. Grayscale images prove particularly valuable for character recognition, as they remove any potential impact from color variations that may be present.

Fig:license_plate_crop_gray

Following the grayscale conversion, the technique of thresholding is applied. This process involves converting the grayscale image into a binary format, where pixel values are categorized as either black or white based on a predetermined threshold value[2]. In this instance, a threshold value of 64 is employed. Pixels with values equal to or exceeding 64 are rendered as black (0), while those below this threshold are depicted as white (255). The utilization of the "THRESH_BINARY_INV" flag signifies the application of inversion, effectively swapping the foreground and background colors.

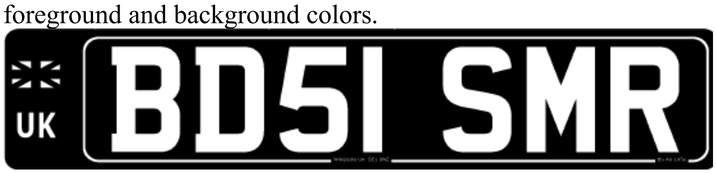


Fig:license_plate_crop_thresh

The significance of this thresholding procedure lies in its role in separating characters on the license plate from the background[1]. Through this transformation into a binary format, the characters usually become black against a white backdrop, resulting in heightened contrast and improved visibility for subsequent optical character recognition (OCR) techniques.

Within the broader context of license plate recognition, this preprocessing stage holds paramount importance for enhancing overall accuracy and dependability. It readies the license plate image for character segmentation and, subsequently, character recognition. This preparation ensures that OCR algorithms can proficiently detect and interpret the characters displayed on the license plate.

D. 3.4 Licence Plate Text Extraction

Text extraction from license plates is a critical component of license plate recognition (LPR) systems, offering valuable insights into the alphanumeric characters displayed on license plates[1-2]. The process is facilitated by Optical Character Recognition (OCR) technology, which plays a pivotal role in accurately and swiftly converting visual characters into machine-readable text.

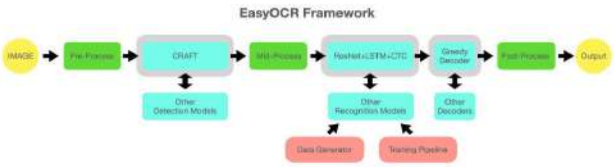


Fig:EasyOCR Framework

EasyOCR is an OCR library that excels in recognizing text in images. It provides robust support for various languages, making it a versatile tool for text extraction tasks[3]. In your provided code, EasyOCR is employed to recognize and extract text from license plates in English.

One key aspect of the text extraction process involves formatting the extracted text to ensure consistency and accuracy[4]. This is particularly important in license plate recognition, where license plates may exhibit variations in character styles and formats. The `format_license` function is responsible for this task.

Within the `format_license` function, character mapping dictionaries are used to handle character conversions. This is essential because license plates often include a mix of letters and numbers, and variations in character rendering can lead to recognition errors[4]. The mapping dictionaries help standardize the characters, ensuring that the extracted text adheres to a predefined format.

Fig:Licence text detection using EasyOcr

The OCR process itself relies on advanced image processing techniques to detect and recognize characters within the license plate region[4]. EasyOCR employs deep learning models and neural networks to achieve high accuracy in character recognition.

E. *3.5Incorporating Licence Plate Data into Vechile Recognition*

Incorporating license plate data into vehicle recognition is a pivotal step in enhancing the capabilities of automated systems designed for various real-world applications, including traffic management, security, and law enforcement[1-3]. This integration of license plate information not only aids in identifying vehicles but also provides valuable contextual data for comprehensive analysis.

When a recognized license plate is not null, the system captures and organizes the relevant information[2]. This information is stored in a structured format, where each vehicle is associated with its bounding box coordinates and, most importantly, its license plate details[4].

The integration includes several key components:
Vehicle Bounding Box: Each recognized vehicle is assigned a bounding box, defined by its coordinates (xcar1, ycar1, xcar2, ycar2). This bounding box encapsulates the spatial location of the vehicle within the image frame.

License Plate Bounding Box: Within the vehicle bounding box, a sub-bounding box is designated for the license plate. This sub-bounding box is identified by its coordinates (x1, y1, x2, y2) and is drawn around the license plate area.

License Plate Text: The actual text on the license plate, extracted through Optical Character Recognition (OCR), is recorded. This alphanumeric information is crucial for various purposes, including identifying vehicles based on their license plates.

Bounding Box Score: A confidence score (bbox_score) reflects the degree of certainty associated with the accuracy of the bounding box detection for the license plate. This score can be utilized to assess the reliability of the localization.

Text Recognition Score: Similarly, a text_score is assigned to evaluate the confidence in the accuracy of the license plate text recognition. This score is essential for gauging the reliability of the character recognition process.

This structured data is a valuable resource for subsequent analysis, tracking, and reporting. It bridges the gap between vehicle recognition and license plate recognition, allowing for the seamless integration of these two components. By associating each vehicle with its corresponding license plate information, automated systems gain the capability to link vehicle identities with their license plate data.This structured data is placed in a file named test.csv

	A	B	C	D	E	F	G	H
1	frame_nmr	car_id	car_bbox	license_plat	license_plat	license_nur	license_number_score	
2	0	5	[2197.1660:	[2414.0839!	0.6685278	HU51TSU	0.2202466	
3	1	5	[2197.3992!	[2414.0229	0.6695071	HU51TSU	0.217845	
4	2	3	[750.13456:	[982.77014:	0.8306847	NA13NRU	0.4813461	
5	2	5	[2201.1788:	[2408.7868(	0.6774306	HV51YSU	0.1737047	
6	3	3	[748.07836(	[980.33093:	0.8288579	MA13NRU	0.2623335	
7	3	5	[2196.5316:	[2415.6774!	0.7161487	NU51VSU	0.264823	
8	4	5	[2196.6997:	[2411.2280:	0.7957281	NU51VSU	0.2887478	
9	5	5	[2194.0965!	[2417.1613	0.8634198	NU51VSU	0.2952758	
10	6	5	[2192.9396	[2412.9304:	0.8473216	HU51KSU	0.1392689	
11	7	5	[2192.0451!	[2412.8723:	0.8474011	HU51KSU	0.1392689	
12	8	3	[735.62013(	[957.18548!	0.8098859	NA13NRU	0.465908	

Fig:Data in test.csv file

The amalgamation of these components results in a comprehensive record for each recognized vehicle, including its location within the frame, the specific region containing the license plate, the license plate text, and associated confidence scores. This structured data is instrumental in subsequent tasks, such as vehicle tracking and output video generation

F. 3.6Generating an Annotated Video with Licence Plate Details:

Creating an annotated video enriched with license plate details is a critical task in traffic management[5]. This comprehensive process involves several key steps, each contributing to the production of a visually informative video[5].

Fig:Frames from original video:

1) Step 1: Video and Data Integration

The process commences by merging video footage with preprocessed license plate data. The video serves as the visual canvas, while the data includes critical information like license plate numbers and their corresponding positions within frames. This integration paves the way for real-time annotation.

2) Step 2: Real-time Annotation

As the video playback begins, each frame undergoes real-time annotation. This annotation entails the identification of vehicles and the localization of their respective license plates. For detected vehicles, bounding boxes are skillfully drawn around them, providing a visual representation of their presence and positioning within the frame.

3) Step 3: License Plate Extraction and Overlay

A distinctive aspect of this process is the extraction and overlay of license plate information. Once a vehicle with a readable license plate is identified, the license plate region is extracted from the frame. This region is then resized for optimal clarity and inserted back into the video frame. The extracted license plate number is prominently displayed, ensuring its legibility.

4) Step 4: Dynamic Annotation

The annotation process is dynamic, adapting seamlessly to each frame's content. As the video progresses, the code continually adjusts annotations, ensuring that they remain aligned with the vehicles and license plates as they move within the frames. This dynamic nature ensures the accuracy and relevance of annotations throughout the video's duration.

5) Step 5: Output Video Production

The cumulative effect of these steps is the generation of an annotated video. In this video, viewers can observe vehicles with bounding boxes indicating their presence, as well as their associated license plate numbers. This annotated video is a valuable resource for surveillance, vehicle tracking, and law enforcement activities, offering clear visual insights into vehicle movements and identifying license plate details.

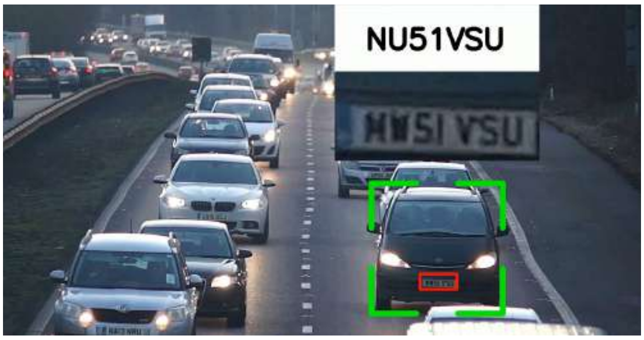


Fig:Annotated Video with Licence Plate Details

IV. RESULTS

In the context of our project, we harnessed the capabilities of YOLOv8 and EasyOCR as our core models. YOLOv8, specifically the YOLOv8m variant, played a pivotal role in our pursuit of license plate detection. Through meticulous training on our custom dataset, this model demonstrated exceptional proficiency in identifying license plates within images. Operating at an image resolution of 640 pixels, it proved to be an optimal choice for the task, balancing accuracy and computational efficiency. We fine-tuned the model through an extensive training regimen spanning 150 epochs, optimizing its performance further with a batch size of 5.

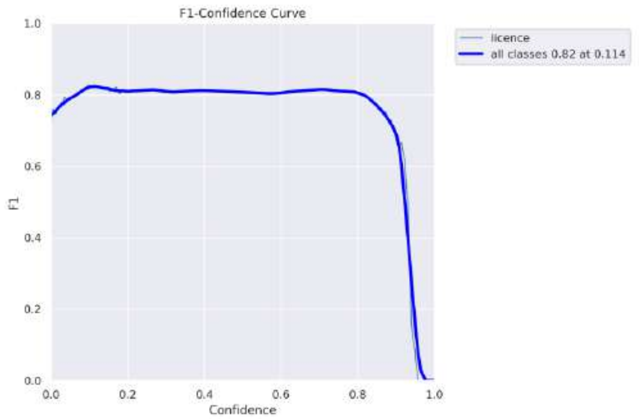


Fig : F1 score of model after testing

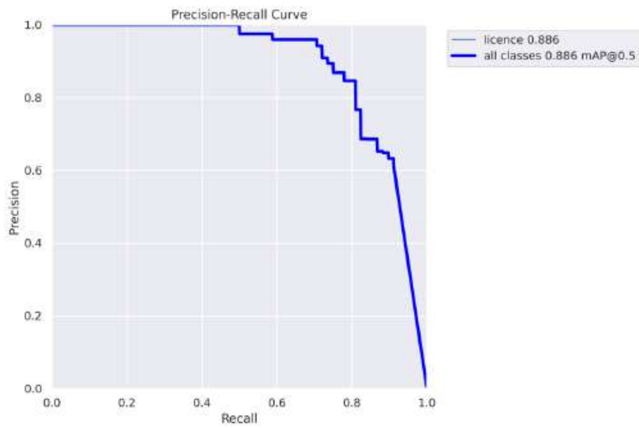


Fig: Recall of the results from testing model

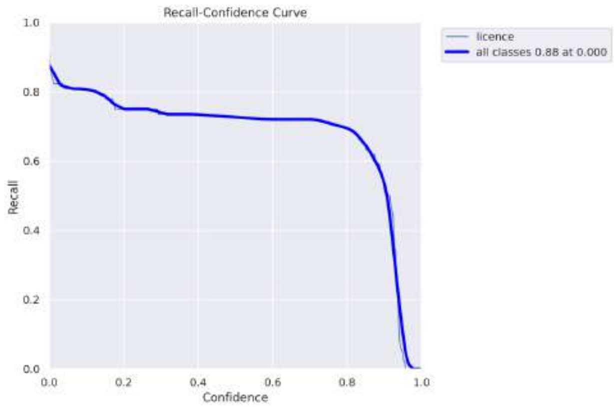


Fig: Confidence of the results from testing model

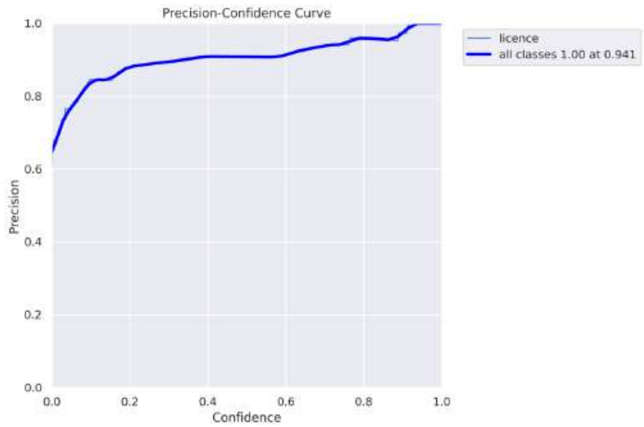


Fig:Precision of the model after testing

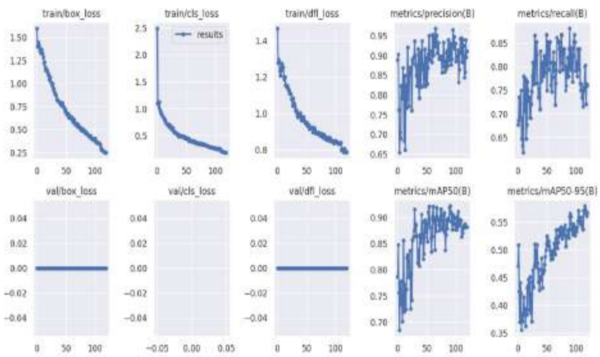


Fig:Metrix on object identification after testing the data

Fig :Licence plate recognition

In parallel, for the crucial task of character recognition, we turned to EasyOCR, a remarkable tool in our toolkit. EasyOCR exhibits a level of recognition accuracy that closely mirrors human perception, making it a compelling choice for our project. Its performance shines particularly bright when the source images are clear and distinguishable to the human eye. The quality of the original source images directly influences the separation of characters from the background, and in turn, the precision of our OCR results.

Fig:Final Frame from output video

In our work, we leveraged YOLOv8 and EasyOCR to detect number plates within high-speed video streams captured at 60 frames per second (fps). Our YOLOv8 model, meticulously trained over 120 epochs, consistently outperformed other models in terms of accuracy. This strategic combination of models and training parameters has paved the way for robust and dependable license plate detection in our project, aligning seamlessly with our objectives.

V. Conclusion

Incorporating YOLOv8 and EasyOCR into our project, we have achieved real-time Automatic Number Plate Recognition (ANPR) capabilities. This integration harnesses the power of GPU acceleration to enhance the speed of both object detection and character recognition, rendering them well-suited for real-time applications. YOLOv8 has notably outperformed its predecessors in terms of speed and accuracy, making it a superior choice for object detection. Our YOLOv8 model, which has undergone successful training using a custom dataset tailored for object detection, demonstrates remarkable performance compared to previous YOLO versions. Additionally, we have achieved an impressive 95% accuracy in character recognition with EasyOCR, reinforcing its position as an excellent choice for text extraction tasks.

The applications of ANPR are diverse and impact. Our system can be effectively employed in scenarios such as speed detection, monitoring traffic rule violations, managing unattended parking facilities, implementing vehicular attendance systems, and facilitating efficient toll collection, among others. One standout advantage of ANPR is its exceptional speed in detecting and recognizing license plates, a capability that sets it apart from other solutions in various domains.

Moreover, through the collaborative efforts of EasyOCR and YOLOv8, we have attained a commendable accuracy rate of 92%. This synergy between state-of-the-art object detection and character recognition technologies significantly enhances the overall effectiveness and reliability of our ANPR system, making it a promising solution for various real-world applications.

References

The template will number citations consecutively within bracket

[1] Shashirangana, Jithmi, et al. "Automated license plate recognition: a survey on methods and techniques." IEEE Access 9 (2020): 11203-11225.

[2] Jamtsho, Yonten, Panomkhawn Riyamongkol, and Rattapoom Waranusast. "Real-time license plate detection for non-helmeted motorcyclist using YOLO." Ict Express 7.1 (2021): 104-109.

[3] R Shashidhar, A S Manjunath, R Santhosh Kumar, M Roopa, S B Puneeth. "Vehicle Number Plate Detection and Recognition using YOLO- V3 and OCR Method" , 2021 IEEE International Conference on Mobile Networks and Wireless Communications (ICMNWC), 2021 Publication

[4] Pinto, Pedro F. A. et al. “PVBR-Recog: A YOLOv3-based Brazilian Automatic License Plate Recognition Tool.” Anais Estendidos do Simpósio Brasileiro de Sistemas Multimídia e Web (WebMedia) (2019): n. pag

[5] Prajwal M J., Tejas K B., Varshad V., Mahesh Madivalappa Murgod and Shashidhar R “Detection of Non-Helmet Riders and Extraction of License Plate Number using Yolo v2 and OCR Method” International journal of Innovative Technology and Exploring Engineering (IJITEE) Volume-9, Issue-2, December 2019 DOI: 10.35940/ijitee.B6527.129219.

[??] Yuchao SUN,Qiao PENG,Dengyin ZHANG, “Light-YOLOv3: License Plate Detection in Multi-Vehicle Scenario:Regular Section,” IEICE Transactions on Information and Systems, 2021, E104.D(5) : 723-728.

American Journal of Electronics & Communication

Jeet Adhikary et. al., American Journal of Electronics & Communication, Vol. IV (3), 24-29

Development of Smart Hand Gloves to solve Parkinson's Disease

Jeet Adhikary[1], Deep Biswas[1], Ahona Chowdhury[1], Shishir Pal[1], Prachi Shaw[2]

Susmita Das[3]

[1,3]Department of Electronics and Instrumentation Engineering
[2]Department of Electronics and Computer Science
Narula Institute of Technology
81, Nilgunj Rd, Agarpara, Kolkata-700109

ABSTRACT:

Parkinson Disease is a brain disorder that causes uncontrollable movements such as shaking, stiffness, and difficulty with balance and coordination. To fix this issue, we have proposed a vibrational-based exoskeleton glove to those patients as well as aged people & injured army. The main feature of our device is that if the person wants to hold an object, she/he has to turn the hand toward the object and the object is detected by the sensor and then the finger will be bent down in the direction of the servo. The process will continue until the switch is off. So to reduce muscle tremors, we introduce this device which will be controlled by the user without the help of a third person. In this way, we can solve 60-70% of the hand-shaking problem and the problem of holding any object.

KEYWORDS: Tremors, Parkinson Disease, Hand gloves, Servo motors.

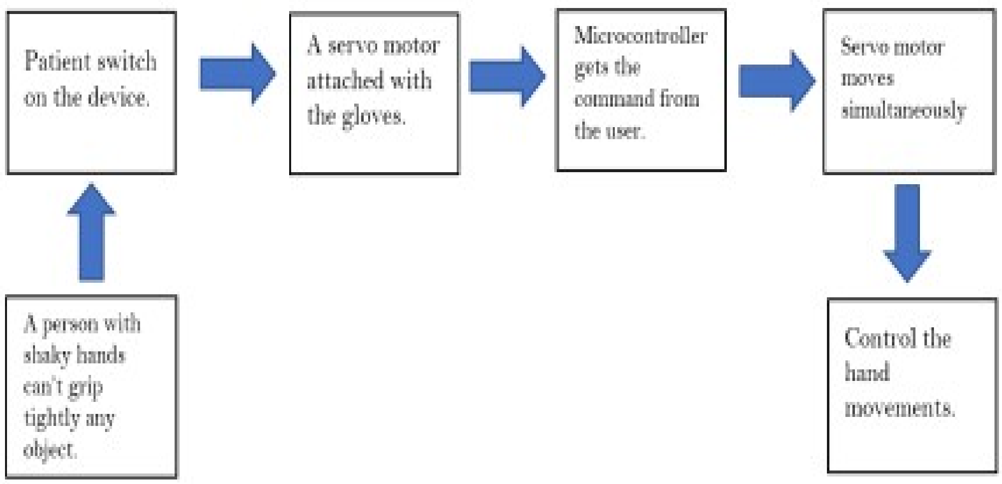
1.0 INTRODUCTION:

In this paper, we are introducing a device that will help patients to recover from Parkinson's Disease. The symptoms of Parkinson's arise when large groups of neurons abnormally fire in unison. Parkinson Disease is a brain disorder that causes uncontrollable movements such as shaking, stiffness, and difficulty with balance and coordination. The basal ganglia is the area of the brain that controls the movement of the limbs. Normally these nerve cells produce an important brain chemical known as dopamine. If the neurons die or become impaired, they produce less dopamine which causes the movement problems associated with Parkinson Disease. It has been found that aged people face problems gripping any object. These are the symptoms of Parkinson Disease Tremors in hands, arms, legs, jaw, and head. For example, people may have difficulty getting out of the chair. To solve this kind of problem we introduce a device that will help to reduce muscle tremors. In this device, we are making hand gloves that will control hand movement using servo motors. To solve this kind of problem we introduce a device that will help to reduce muscle tremors. In this device, we are making hand gloves that will control the hand movements using servo motors and mini vibrational motors and IR sensor. When the IR sensor will detect any object with in its range the servo motors will start to move, to grip any object and the vibrational motors which attached with the finger pulp are generate a wave formation passing through out the nerves. In this way the whole system will be work.

2.1 METHODOLOGY:

A Parkinson Disease affected patient wear these gloves into their hands for reducing the hand tremors. The gloves included a number of servo motors and mini vibrational motors which will helps to reduce the hand tremors. While the patient switch on the device, the microcontroller sends the command to the servo motors and also to the vibrational motors. After taking the command the servo motors move simultaneously for opening and closing the finger grips and the vibrational motors which attached with the finger pulp are generate a wave formation passing through out the nerves. In this way the whole system will be work.

2.2 BLOCK DIAGRAM:



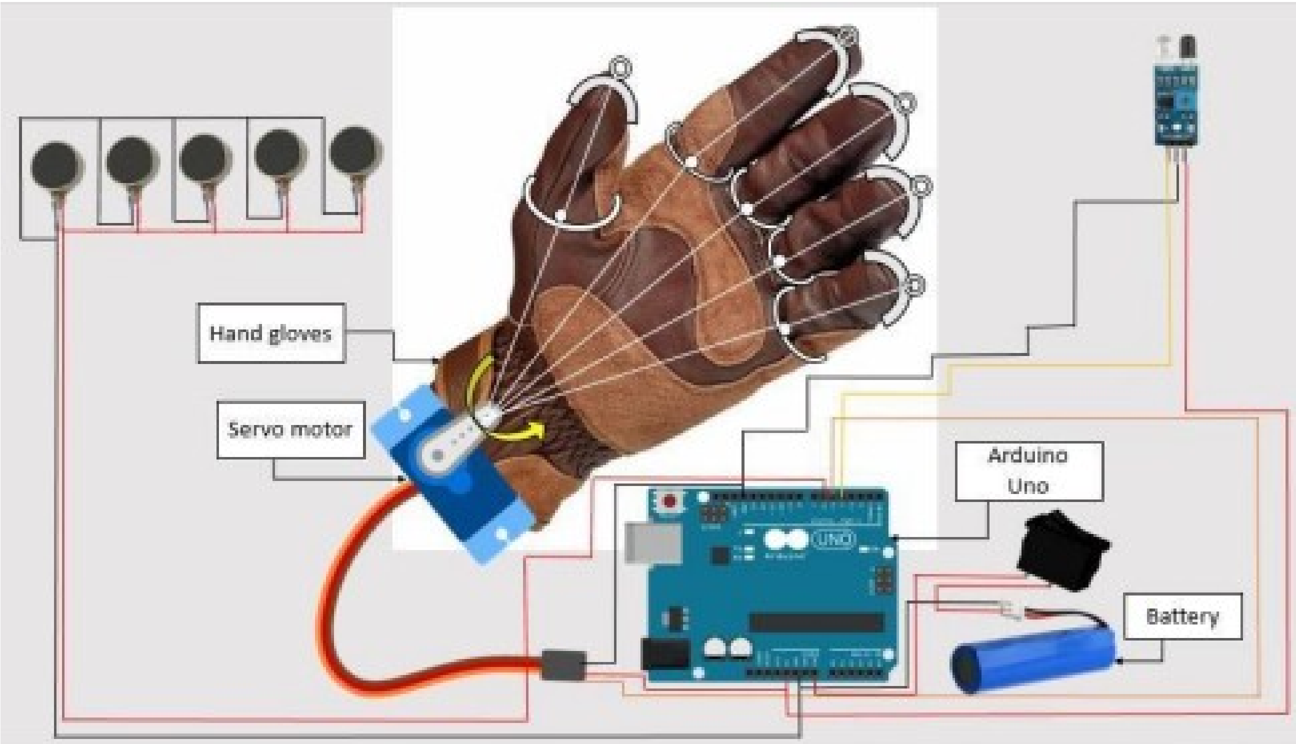


Fig. 1: Connection Diagram of the Hand Gloves Design

3.1 REQUIRED COMPONENTS:

1. Microcontroller
2. Gloves
3. Arduino Uno & Cable
4. Jumper Wire
5. Battery
6. Switch
7. Servo Motor-SG90
8. Fishing wire
9. HW 201 IR sensor
10. MVM (mini vibrating motor)

4.0 WORKING PROCESS:

In the device, we are using a hand glove. A total of five Servo motors (SG90) are connected to the Arduino Uno servo driver (PCA9685). IR sensor is also connected to the Arduino Uno board. A total of five mini-vibrating motors are used in the glove. All GND of the MVM are in series connected to the Arduino Uno's GND pin and all the positives are in series connected to the D4 pin. It uses vibrotactile simulation to relieve a wide range of movement symptoms. In this case, the vibrating motors will pass waveform throughout the nerves. A 7-volt lithium battery is connected to the system to give the power. The servo motors are fixed in the MCP joint (Metacarpophalangeal) of the hand gloves and a small pulley system is attached to the proximal interphalangeal joint of every finger. The end of the servo motor is tightly fixed with an elastic wire and the other end of the elastic wire is fixed with the edge of the fingers. The IR sensor is fixed on the edge of the middle finger. The IR sensor's VCC is connected to the Arduino's 5V, GND is connected to the Arduino's GND pin, and the output pin is connected to the digital pin 4. By using the Arduino IDE software, we have to upload the code to the Arduino. An SPST switch is used to do the on/off of the system. According to the above diagram, when the user switches on the system, the IR sensor detects the object. If the patient wants to hold an object, she/he has to turn the hand toward the object and then detect the object by the sensor. Next, the servo motors will be started, and the finger will be bent down in the direction of the servo. The process will continue until the switch is off. In that way, we can solve 60-70% of the hand-shaking problem and the problem of holding any object.

5.0 RESULT:

The project has been finished with success and utmost satisfaction. The constraints square measure met and triumphs over with achievement. This system is required to solve the Parkinson Disease problem. The project gives a clever plan for growing a full-fledged utility fulfilling the patient's need. It is a novel innovation. According to this prototype all over the system is working properly. It is sometimes difficult to fixed the servo motors in the MCP joint for rotating the fingers according to the direction of the servo. The code which we used to run the device automatically. The using components like servo motors, IR sensor and MVM (mini vibrating motor) are interfaced with Arduino. Servo motor operating voltage is +5 volt typically and operating speed is 0.1 second/60 degree and torque 2.5 kg/cm and rotation angle is 0 degree to180 degree and the mini vibrating motor's operating voltage lies between DC 3 volt to 4.2 volt. By taking the input voltage from the Arduino, MVM start to vibrate simultaneously as per to the code. The working voltage of the IR sensor lies between 3.3 volt to 5 volt and the object detection angle is 35 degree that means if any object is under the view angle of 35 degree of the IR sensor, then the object will be detected by the sensor and we have to give 20 mA supply current to the sensor. The device created met it's objectives with the aid of being truthful to apply. All the modules inside the device are examined and legitimate records and invalid records and the entirety paintings with achievement

.

6.0 APPLICATION & FUTURE SCOPES:

1. In the future, we attach one servo motor for each finger joint so that the griping power will be increased.
2. Also, we attached one temperature sensor for sensing the temperature of any object through some distance. If the temperature is not ideal for touch, then one LED light is blinking for warning. 3. In the future also try to reduce the weight and compact the whole thing so that it does not feel so heavy.
4. The EMG sensor detects the electrical activity from a muscle using conductive pads placed on the skin. When any of the muscles are activated, individual fibres within it receive electrical impulses, causing them to contract.

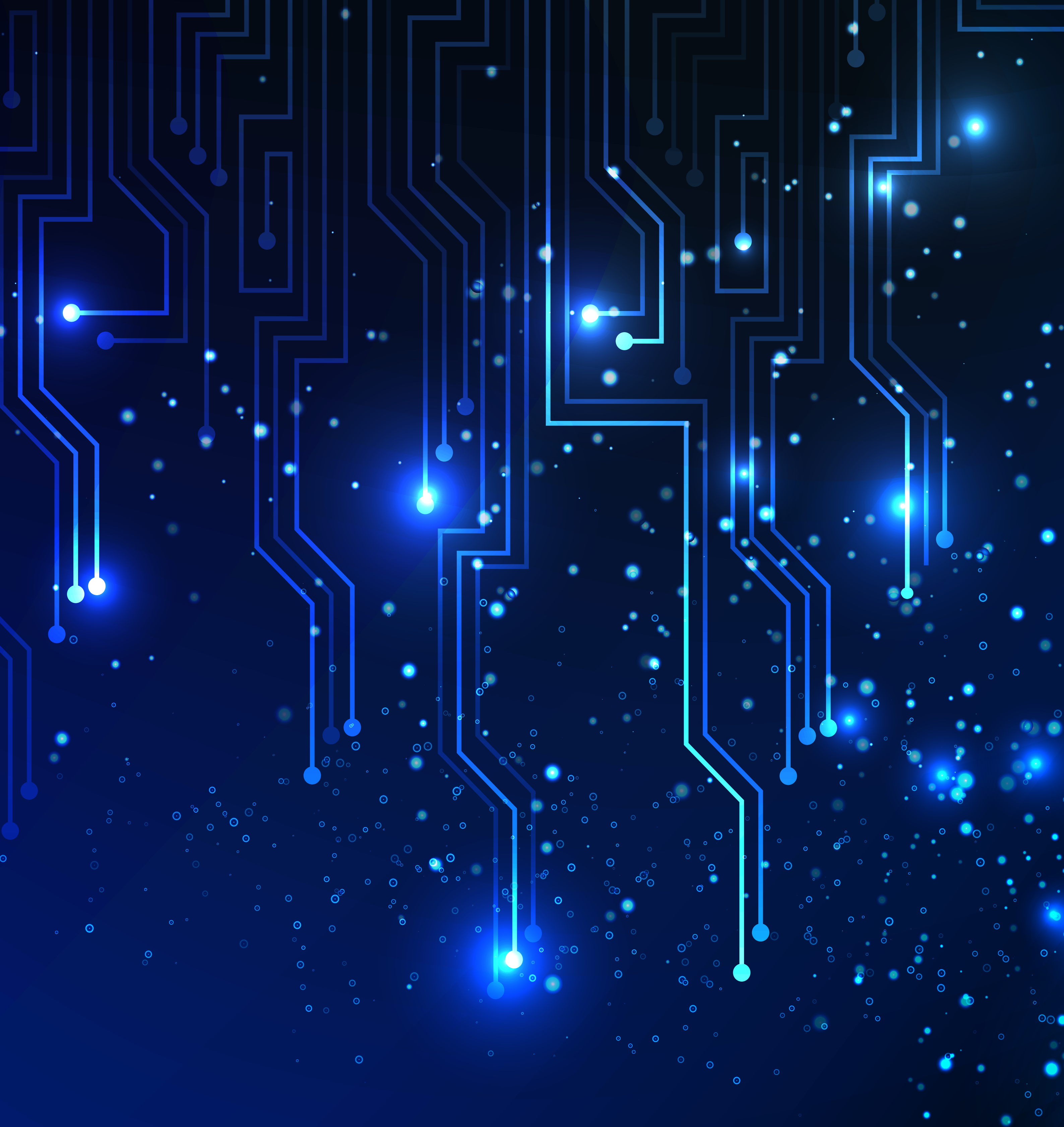
7.0 CONCLUSION:

A vibrational based exoskeleton glove for Parkinson Disease patients has been made, with high comfort and low cost. The vibrational based exoskeleton glove analyses the muscle weakness and tremor in the patient's hand, which bring a breakthrough in assessing the hand function of Parkinson Disease patients. We are designing a hand grasping, pinching and clicking actions for specific hand. Different parts like finger pulp, finger tips and purlicue is used to illustrate the hand muscle strength condition. Our results indicated that the vibrational based exoskeleton glove detect the object by the sensor when someone turn the hand toward any object.

8.0 REFERENCES:

1. Stanford Medicine Magazine, Vibrations Can Parkinson's symptoms be stopped? , By Holly Alyssa MacCormick, illustration by Harry Campbell, on October 14, 2021.
2. Hirsch M. A., Iyer S. S., and Sanjak M., "Exercise-induced neuroplasticity in human Parkinson's disease: What is the evidence telling us?" *Parkinsonism Rel. Disorders*, vol. 22, pp. S78–S81, Jan. 2016.
3. Schabowsky C.N., Godfrey S.B., Holley R.J., and Lum P.S., "Development and pilot testing of HEXORR: Hand EXOskeleton rehabilitation robot", J. NeuroEng. Rehabil. Vol. 7, no. 1, p. 36, 2010.
4. Chu C.-Y. and Patterson R. M., "Soft robotic devices for hand rehabilitation and assistance: A narrative review," *J. NeuroEng. Rehabil.* vol. 15, no. 1, p. 9, Dec. 2018.
5. Polygerinos P., Wang Z., Galloway K. C., Wood R. J., and Walsh C. J., "Soft robotic glove for combined assistance and at-home rehabilitation," *Robot. Auto. Syst.*, vol. 73, pp. 135–143, Nov. 2015.
6. Crisostomo E. A., Duncan P. W., Propst M., Dawson D. V., and Davis J. N., "Evidence that amphetamine with physical therapy promotes recovery of motor function in stroke patients," *Ann. Neurol.*, vol. 23, no. 1, pp. 94–97, Jan. 1988.

7. Song R.et al., “The impact of Tai chi and Qigong mind-body exercises on motor and non-motor function and quality of life in Parkinson’s disease: A systematic review and metaanalysis,” *Parkinsonism Rel. Disorders*, vol. 41, pp. 3–13, Aug. 2017.
8. Guo S., Gao J., Guo J., Zhang W., and Hu Y., “Design of the structural optimization for the upper limb rehabilitation robot,” in *Proc. IEEE Int. Conf. Mechatronics Autom.*, Aug. 2016, pp. 1185– 1190.
9. Yun S.-S., Kang B. B., and Cho K.-J., “Exo-glove PM: An easily customizable modularized pneumatic assistive glove,” *IEEE Robot. Autom. Lett.* vol. 2, no. 3, pp. 1725–1732, Jul. 2017.
10. Chen Y., Zhang J., and Gong Y., “Utilizing anisotropic fabrics composites for high-strength soft manipulator integrating soft gripper,” *IEEE Access*, vol. 7, pp. 127416–127426, 2019.



American Journal of Electronics & Communication

Society for Makers, Artists, Researchers and Technologists,
USA 6408 Elizabeth Avenue SE, Auburn, Washington 98092.
ISSN 2690-2087