प्रो. रजनीश जैन
सचिव
Prof. Rajnish Jain
Secretary

विश्वविद्यालय अनुदान आयोग
University Grants Commission
(मानव संसाधन विकास मंत्रालय, भारत सरकार)
(Ministry of Human Resource Development, Govt. of India)
बहादुरशाह ज़फ़र मार्ग, नई दिल्ली-110002
Bahadur Shah Zafar Marg, New Delhi-110002
Ph.: 011-23236288/23239337
Fax: 011-2323 8858
E-mail: secy.ugc@nic.in

D.O. No.75-1/2018(e-Gov./TAC) 2nd August, 2019

Respected Madam/Sir,

The Ministry of Human Resource Development, Government of India has entrusted the Information and Library Network Centre (INFLIBNET) an Inter University Centre of University Grants Commission, to provide Plagiarism Detection Software (PDS) to all Universities/Institutions including Private Universities free of cost. Accordingly, INFLIBNET Centre has subscribed the PDS, URKUND (by M/s Prio Infocenter, Sweden) through global tender process. As per the plan, the trial access of PDS to all the Universities/ Institutions will start from 2nd August, 2019 for one month and final subscription to the access of PDS for all Universities/Institutions will start from 1st September, 2019.

In this regard, you are requested to provide the details regarding number of faculty members, number of research scholars and University Coordinator (along with email and contact details) at **pds.tech@inflibnet.ac.in** so that admin account for your University can be created. Shri Manoj Kumar K, Scientist- D(CS), INFLIBNET may be contacted for further details at **manoj@inflibnet.ac.in**.

We solicit your kind cooperation in smooth implementation of the software in all universities.

With kind regards,

Sincerely yours,

(Rajnish Jain)

The Vice Chancellor of all Universities.

Registrar
Quantum University

Information and Library Network Centre
(An Autonomous Inter-University Centre of UGC)
सूचना एवं पुस्तकालय नेटवर्क केन्द्र
(विश्वविद्यालय अनुदान आयोग का स्वायत्त अंतर विश्वविद्यालय केन्द्र)

INFLIBNET

Prof J P Singh Joorel
Director

प्रो जे पी सिंह जूरैल
निर्देशक

July 23, 2019

Dear Vice Chancellor/Director,

As you are aware that Ministry of Human Resource Development, Govt. of India is keen to enhance the quality of research in Indian Universities/Institutions and prevent the plagiarism in research/academic publications. In this regards I am happy to inform that MHRD has entrusted "**Information and Library Network Centre (An Autonomous Inter University Centre of University Grants Commission) Gandhinagar, Gujarat**" to provide the **Plagiarism Detection Software (PDS),** to all the Universities/Institutions including private Universities through centrally funded scheme. Accordingly, **INFLIBNET Centre has subscribed the PDS (URKUND by M/s. Prio Infocenter, Sweden) through global tender process**. As per the plan, the trial access of PDS to all the Universities/Institutions will start from 1st August, 2019 for one month and final subscription to the access of PDS for all Universities/Institutions will start from 1st September, 2019.

The INFLIBNET Centre is in process of implementation of PDS in all the Universities. In this regards you are requested to kindly nominate the University/Institute Coordinator and instruct him/her to immediately contact the INFLIBNET Centre at **pds.help@inflibnet.ac.in** and provide the details regarding number of faculty members, number of registered research scholars and contact details of University/Institute Coordinator so that admin account for your University/Institute can be created. For further details Sh. Manoj Kumar K, Scientist D (CS), may be contacted at **manoj@inflibnet.ac.in** or **pds.tech@inflibnet.ac.in**.

If your University has already submitted the required information, kindly IGNORE it.

With regards

(Prof J P Singh Joorel)

Registrar
Quantum University

Infocity, P.B. No. 4, Gandhinagar - 382007, Gujarat, INDIA
इन्फोसीटी, पो.बो. नं.४, गांधीनगर - ३८२००७, गुजरात (भारत)
Ph.: +91-79-23268201, Fax : +91-79-23268111, Email: director@inflibnet.ac.in, Web : http://www.inflibnet.ac.in

F.No 8-12/2018-TEL
Government of India
Ministry of Human Resource Development
Department of Higher Education
(TEL Division)
******

426-C, Shastri Bhawan,
New Delhi dated 29th Jul, 2019

Subject : Implementation of Anti-Plagiarism Detection software in the Universities/ Institutions – regarding.

The undersigned is directed to state that Ministry of Human Resource Development, Govt. of India is keen to enhance the quality of research in Indian Universities/Institutions and prevent the plagiarism in research/academic publications. In this regard, MHRD has entrusted "Information and Library Network Centre (An Autonomous Inter University Centre of University Grants Commission) Gandhinagar, Gujarat" to provide the Plagiarism Detection Software (PDS), to all the Universities/Institutions including private Universities through centrally funded scheme. Accordingly, INFLIBNET Centre has subscribed the PDS (URKUND by M/s. Prio Infocenter, Sweden) through global tender process. As per the plan, the trial access of PDS to all the Universities/Institutions will start from 1st August, 2019 for one month and final subscription to the access of PDS for all Universities/Institutions will start from 1st September, 2019.

2. The INFLIBNET Centre is in the process of implementation of PDS in all the Universities/Institutions. It is therefore requested to kindly direct the institutes under your administrative control to nominate the Institute Coordinator and instruct him/her to immediately contact the INFLIBNET Centre at pds.help@inflibnet.ac.in and provide the details regarding number of faculty members, number of registered research scholars. Contact details of Institute Coordinator may kindly be given to INFLIBNET so that admin account for Institute can be created. For further details Sh. Manoj Kumar K, Scientist D (CS), may be contacted at manoj@inflibnet.ac.in or pds.tech@inflibnet.ac.in.

Chairman Sectt.
AICTE
31 JUL 2019
Dy. No. 7425

M Narayanan
(Malathi Narayanan)
Deputy Secretary (TEL)
Tel no. 011-23385220

Registrar
Quantum University

Quantum UNIVERSITY

Vice Chancellor <vicechancellor@quantumuniversity.edu.in>

Reg: Providing Plagiarism Detection Software (PDS) to all the Universities/ Institutions

4 messages

PDS Survey <pds.tech@inflibnet.ac.in> Mon, Oct 21, 2019 at 5:40 PM
To: vicechancellor@quantumuniversity.edu.in

Dear **Prof. Vivek Kumar**,

Greeting from INFLIBNET Centre..!!

As discussed, INFLIBNET Centre, an IUC of UGC, Min.of HRD, Government of India, was sending request to fill your requirement for getting Plagiarism Detection Software (PDS) since July-2019. In this regard, the official communications were sent from the Secretary, UGC as well as MHRD (attached).

We are glad to inform that the project ShodhShuddhi (formally known as PDS) was launched on 21st September 2019 by Hon'ble Minister of HRD, Shri Ramesh Pokhriyal 'Nishank'(http://shodhshuddhi.inflibnet.ac.in/). But, we could not get the requirements such as No of regular faculty, number of full time P.hD Scholar etc for your esteemed University/Institution.

We are once again requesting you to complete the requirements at the earliest to create University coordinator accounts for using URKUND software.

Please use the given URL for submitting the data.

http://pds.inflibnet.ac.in/login

Username: PDS-I-2019-955

One Time Password

With regards

For, Team PDS

---

3 attachments

Registrar
Quantum University

Letter UGC Secretary.jpg
64K

Anti Plagiarism Detection Software-MHRD.pdf
209K

Director INFLIBNET_Letter-VC-letterhead.pdf
721K

Vice Chancellor <vicechancellor@quantumuniversity.edu.in> Mon, Oct 21, 2019 at 5:41 PM
To: PDS Survey <pds.tech@inflibnet.ac.in>

Thanks sir for prompt reply. We shall complete the task tomorrow only.
regards
[Quoted text hidden]
--

Prof. Vivek Kumar,
Vice Chancellor,

Quantum UNIVERSITY
Dehradun-Roorkee Highway, Roorkee, INDIA
Phone +919991881333 (O), +919760071971 (R)
Email: vicechancellor@quantumuniversity.edu.in
Web: www.quantumuniversity.edu.in

PDS Survey <pds.tech@inflibnet.ac.in> Mon, Oct 21, 2019 at 6:15 PM
To: Vice Chancellor <vicechancellor@quantumuniversity.edu.in>

Dear **Prof. Vivek Kumar**,

Greetings from INFLIBNET Centre..!!

Thanks for submitting the data for PDS.

Please be noted that after submitting the data, we will forward the **activation link of URKUND account** to the University Coordinator's **(UC)** account **(vinod.mishra.agr@quantumeducation.in)** to activate it within 96 hours, accordingly **UC** will be able to add more **Users (i.e. PhD,Post Doctoral researchers & Faculty members)** themselves. If its not activated within the said time-frame then it will be expired. Therefore, please let us know so we can assist you in further formalities to be carried out if not activated the link on time.

And, kindly check regularly your **Inbox/Spam/Junk folders** for the activation link from **noreply@urkund.se** (URKUND).

Hence, the **UC** should be able to create accounts for those who are pursuing **PhD** and **Post Doctoral researchers** as well as for **Faculty members**.

Kindly find the attached files of **URKUND** user guide for your reference.

Thanking you

For, Team PDS
[Quoted text hidden]
--
Thanks & Regards
PDS Team.!

---

2 attachments

URKUND - Admin Guide.pdf
1401K

URKUND - Brief Guide to Get Started_Mail11.pdf
1678K

Vice Chancellor <vicechancellor@quantumuniversity.edu.in> Thu, May 19, 2022 at 2:02 PM
To: Naveen Rana <naveenrana.me@quantumeducation.in>

PFA
[Quoted text hidden]
--
Prof. Vivek Kumar
Vice Chancellor

Quantum University
Campus: 22 Milestone, Roorkee - Dehradun Highway (NH 73)
Roorkee - 247662
Uttarakhand.

Mobile: +91-9991881333 (O), +91 9760071971(R)

www.quantumuniversity.edu.in

Registrar
Quantum University

Quantum UNIVERSITY
ROORKEE, INDIA

---

3 attachments

Letter UGC Secretary.jpg
64K

Anti Plagiarism Detection Software-MHRD.pdf
209K

Director INFLIBNET_Letter-VC-letterhead.pdf
721K

Registrar
Quantum University

Quantum UNIVERSITY

Vice Chancellor <vicechancellor@quantumuniversity.edu.in>

Fwd: Reg. URKUND Id creation/University admin account

3 messages

Vinod Kumar MIshra <vinod.mishra.agr@quantumeducation.in> Thu, Oct 24, 2019 at 2:00 PM
To: "Dr. Rahul Sharma" <registrar@quantumuniversity.edu.in>
Cc: Vice Chancellor <vicechancellor@quantumuniversity.edu.in>

---------- Forwarded message ---------
From: **PDS Survey** <pds.help@inflibnet.ac.in>
Date: Thu, Oct 24, 2019 at 1:57 PM
Subject: Reg. URKUND Id creation/University admin account
To: PDS Survey <pds.tech@inflibnet.ac.in>
Cc: Manoj Kumar K <manoj@inflibnet.ac.in>

Dear **University Coordinators**,

Greetings from INFLIBNET Centre..!!

Thanks for submitting the data for PDS (ShodhShuddhi/URKUND) recently. We are in the process of sending the **URKUND Id creation/University admin accounts** soon to activate it within 96 hours, accordingly **UC** will be able to add more **Users (i.e. PhD,Post Doctoral researchers & Faculty members)** themselves. If its not activated within the said time-frame then it will be expired.Therefore, our humble request you to please activate it upon receiving the activation link.

In this regard, kindly check regularly your **Inbox/Spam/Junk folders** for the activation link from **noreply@urkund.se** (URKUND).

Kindly find the attached files of **URKUND** user-guide for more information regarding creation of **Receiver** and **Submitter** accounts.

Please do not hesitate to contact us for any questions or concerns you may have.

With regards

For, Team PDS

Registrar
Quantum University

--
Dr. Vinod Kumar Mishra

Associate Professor
Department of Agriculture Studies
Quantum University, Roorkee
Mob:7579043050

---

2 attachments

URKUND - Admin Guide.pdf
1401K

URKUND - Brief Guide to Get Started_Mail11.pdf
1678K

Vice Chancellor <vicechancellor@quantumuniversity.edu.in> Sat, Apr 17, 2021 at 11:49 AM
To: Neeraj Sharma <library@quantumeducation.in>, "Dr. Abdullah Malik" <abdullah.qsb@quantumeducation.in>

[Quoted text hidden]
--
Prof. Vivek Kumar
Vice Chancellor

Quantum University
Campus: 22 Milestone, Roorkee - Dehradun Highway (NH 73)
Roorkee - 247662
Uttarakhand.

Mobile: +91-9991881333 (O), +91 9760071971(R)

www.quantumuniversity.edu.in

Quantum UNIVERSITY ROORKEE, INDIA

---

2 attachments

URKUND - Admin Guide.pdf
1401K

URKUND - Brief Guide to Get Started_Mail11.pdf
1678K

Registrar
Quantum University

Vice Chancellor <vicechancellor@quantumuniversity.edu.in> Thu, May 19, 2022 at 2:04 PM
To: Naveen Rana <naveenrana.me@quantumeducation.in>

PFA

---------- Forwarded message ---------
From: **Vinod Kumar MIshra** <vinod.mishra.agr@quantumeducation.in>
Date: Thu, Oct 24, 2019 at 2:00 PM
Subject: Fwd: Reg. URKUND Id creation/University admin account
To: Dr. Rahul Sharma <registrar@quantumuniversity.edu.in>
Cc: Vice Chancellor <vicechancellor@quantumuniversity.edu.in>

[Quoted text hidden]

[Quoted text hidden]

---

2 attachments

URKUND - Admin Guide.pdf
1401K

URKUND - Brief Guide to Get Started_Mail11.pdf
1678K

Registrar
Quantum University

DrillBit

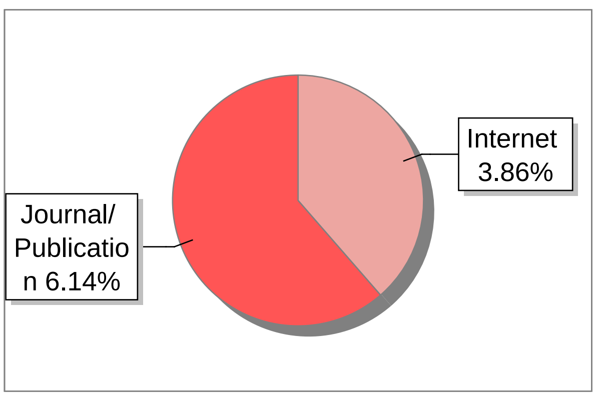
The Report is Generated by DrillBit Plagiarism Detection Software

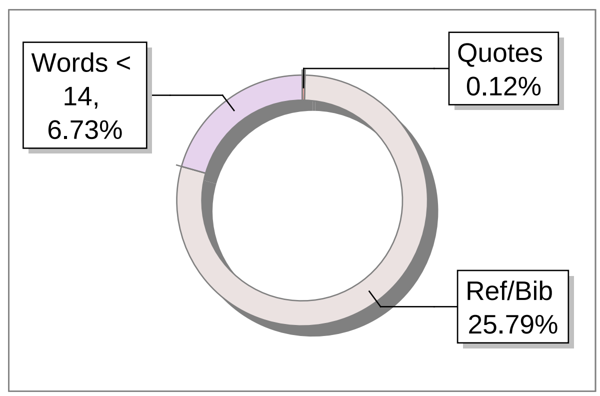
Submission Information

Author Name	Shivansh Chauhan
Title	Organic Farming
Paper/Submission ID	1473638
Submitted by	shivani.agr@quantumeducation.in
Submission Date	2024-02-28 11:50:57
Total Pages	6
Document type	Research Paper

Result Information

Similarity **10 %**





Exclude Information

Quotes	Not Excluded
References/Bibliography	Excluded
Sources: Less than 14 Words %	Not Excluded
Excluded Source	**0 %**
Excluded Phrases	Not Excluded

Database Selection

Language	English
Student Papers	Yes
Journals & publishers	Yes
Internet or Web	Yes
Institution Repository	Yes

A Unique QR Code use to View/Download/Share Pdf File

Registrar
Quantum University

DrillBit

DrillBit Similarity Report

10	11	A	A-Satisfactory (0-10%) B-Upgrade (11-40%) C-Poor (41-60%) D-Unacceptable (61-100%)
SIMILARITY %	MATCHED SOURCES	GRADE	

LOCATION	MATCHED DOMAIN	%	SOURCE TYPE
1	Fresh Water Pollution Dynamics and Remediation	2	Publication
2	www.pw.live	1	Internet Data
4	abnews-wire.blogspot.com	1	Internet Data
6	Study of the behavior of Euglena viridis, Euglena gracilis and Lepadella patella by Podwin-2017	1	Publication
10	bmcreview.org	1	Internet Data
11	cgclimatechange.com	1	Publication
12	cropj.com	1	Publication
13	Dementia Caregivers in Germany and Their Acceptance of New Technologies for Care by Kramer-2013	1	Publication
14	docview.dlib.vn	1	Publication
16	religiondocbox.com	1	Internet Data
17	Volatile organic compounds and formaldehyde in nature, wood and wood based panel by Edmon-2006	1	Publication

Registrar
Quantum University

Organic Nutrient Resources

Shivansh Chauhan[1]

Student of B.sc Agriculture, Quantum School of Agricultural Studies

Quantum University, Roorkee, Uttarakhand, India 247667

Chauhanshivansh03@gmail.com

Abstract: - Organic nutrient resources are materials that are produced organically and give humans, animals, and plants the nutrients they need. These resources are essential for encouraging sustainable agriculture, preserving healthy ecosystems, and enhancing human health. In addition to organic food sources like fruits, vegetables, and grains, organic nutrient resources also include organic fertilizers. We will look at the advantages of organic nutrient resources and how they might help with biofortification in this essay. Organic fertilizers are a type of organic nutrient resource that provides plants with the necessary nutrients. They are made from natural materials such as bone meal, compost, animal dung, and animal manure. They are intended to increase soil fertility and encourage the growth of plants. As an important substitute for synthetic fertilizers, which can harm the environment by contaminating waterways and increasing greenhouse gas emissions, organic fertilizers are recommended. By strengthening soil structure, increasing organic matter, and encouraging the development of helpful microorganisms, organic fertilizers raise the quality of the soil.

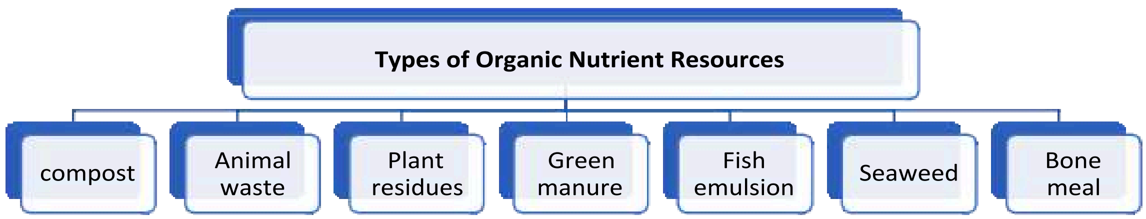
Keywords: - *Organic Nutrients, Pathogens, Compost, Breeding.*

INTRODUCTION: - Organic nutrient resources are an important aspect of agriculture and sustainable food production. They are developed from natural materials for example animal manure, compost, and plant residues. These resources offer a variety of vital nutrients, such as micronutrients, phosphorus, potassium, and nitrogen, which are necessary for plant growth and development. Resources for organic nutrients offer several benefits over synthetic fertilizers. Firstly, they improve soil health by increasing the organic matter content of soil, which enhances soil structure, water-holding capacity, and nutrient availability. (PW Westerman, JR Bicudo 215-221, 2005) Secondly, they reduce the need for synthetic fertilizers and thus decrease the detrimental effects connected to their production and use, such as greenhouse gas emissions and pollution. Thirdly, in general, they cost less than synthetic fertilizers, particularly for small-scale farmers.

However, organic nutrient resources also have some limitations. For example, their nutrient content can be variable and may not always meet crop requirements. They can also be more difficult to transport and apply than synthetic fertilizers, particularly in large-scale farming operations. Furthermore, the use of organic nutrient resources can lead to environmental problems if not managed properly, such as nutrient leaching and contamination of water bodies. (Chanyarat Paungfoo-Lonhienne, Jozef Visser,2012)

Types of Organic Nutrient Resources

Organic nutrients are exactly that-nutrients developed from living organisms or their waste products. They are essential for the rapid growth and improvement of plants and animals. Some types of organic nutrient resources include:



1. **Compost:** Compost is a mixture of decaying organic matter that is used as a fertilizer. It is made from a selection of organic materials, like food scraps, yard waste, and manure. (RS HARKAL, AV MANWAR Romanian Journal of Biophysics 32 (1), 2022).
2. **Animal waste:** Animal waste, such as chicken manure, cow manure, and horse manure, is an abundant source of organic nutrients. It is frequently utilized as a fertilizer in agricultural settings.
3. **Plant residues:** Additional sources of organic nutrients include plant leftovers like leaves, stems, and roots. They can either be integrated to improve soil structure and absorb nutrients fertility, or they can be left on the soil's surface to break down and enrich the soil. (Jian Cui, Jianwei Cui, Jinfeng Li, Wei Wang, Bin Xu, John Yang,2023).
4. **Green manure:** This particular kind of cover crop is planted with the intention of enhancing soil fertility. The process of growing particular plants—usually legumes or particular grasses—and then adding them to the soil while they are still green and actively growing is known as "green manure."

5. **Fish emulsion:** Fish waste is used to make fish emulsion, a liquid fertilizer. It is frequently utilized in organic gardening and is an excellent resource for potassium, phosphorus, and nitrogen. (Sukor A, Qian Y, Davis JG,2023).
6. **Seaweed:** Micronutrients and trace elements can be found in seaweed. It can be used as fertilizer and as a soil conditioner. It is true that seaweed has long been considered a valuable resource and is an excellent source of organic nutrients. (Wickham A, Davis JG, 2023).
7. **Bone meal:** Crushed animal bones are used to make bone meal, which is high in calcium and phosphorus. It is frequently applied as fertilizer to vegetables and flowering plants. (Mahmudul Islam Piash, Koki Uemura, Takanori Itoh,2023.

Contamination of organic nutrient Resources

Organic nutrient resources, such as compost, manure, and sewage sludge, can contain a type of contaminants. These contaminants can include:

1. **Heavy metals:** It is possible regarding heavy metals such as lead, cadmium, mercury, and arsenic to be present in organic nutrient resources. A source of these metals is variety of places, including pesticide residues, automobile exhaust, and industrial waste.
2. **Pathogens:** Organic nutrient resources can contain pathogens such as bacteria, viruses, and parasites. These may have been produced by animal or human waste. and, if improperly handled, can endanger both human and animal health. (Pramod K Pandey, Philip H Kass, 2014).
3. **Pesticides:** Organic nutrient resources can contain pesticide residues from agricultural use. Human health and the environment may be harmed by these residues.
4. **Organic chemicals:** Organic nutrient resources can contain organic chemicals such as polycyclic aromatic hydrocarbons (PAHs) and polychlorinated biphenyls (PCBs). These materials could come from polluted soil or industrial waste, among other places.

To minimize the risk of contamination, it is necessary to properly manage and treat organic nutrient resources before using them as fertilizer. This can include composting, pasteurization, and other forms of treatment to reduce pathogens and harmful compounds. Additionally, it's critical to source organic nutrients correctly and to ensure that they come from reliable, secure sources. (E Bloem, A Albihn, J Elving, L Hermann, 225-242, 2017)

Table. Different contamination with their source, impact, and concerns.

Name of Contamination	Source	Impacts	Concerns
Organic Matter	Effluents from various enterprises and constructed areas.	Reduces O level of rapid decomposition, impacting aquatic life.	The rate of biological oxygen breakdown, which influences aquatic life demand (BOD), dissolved oxygen (DO).
Pathogens (Microbes)	Sewage and Livestock.	Disease spread through polluted drinking water and supplies.	Treatment with antibiotics and anti-parasitic drugs.
Nutrients	Agricultural activity runoff and industrial waste.	Eutrophication is the growth of algae, which eventually decomposes, depleting water of oxygen.	Total Nitrogen (N) and Phosphorus (P).
Salinization	Drained from alkaline soils, on salt water irrigation	The presence of salt in soils can lead to the death of crops or decrease yields.	Treatment with EC, pH, and sodium toxicity.
Toxic organic compounds	Industrial, Agricultural mining, and Residential activities.	Organic pollutant residues at trace level in soil, water, air, and even food can be hazardous to human and environmental health.	Pesticides (lindane, DDT, PCP, Aldrin, Endrin, Isodrin, and Dieldrin, etc.

Conclusion

In conclusion, organic nutrient resources are two complimentary methods that contribute to sustainable agriculture and improved nutrition. Organic nutrient resources enhance soil fertility and promote sustainable farming practices, while bio-fortification focuses on developing crops with enhanced nutrient profiles. By combining these approaches, we can work towards a more sustainable and nutritious food system, addressing both environmental and nutritional challenges.

References

1. Chanyarat Paungfoo-Lonhienne, Jozef Visser, Thierry GA Lonhienne, Susanne Schmidt Plant and Soil 359, 1-18, 2012.
2. PW Westerman, JR Bicudo, Management considerations for organic waste use in Agriculture, Bioresource Technology 96 (2), 215-221, 2005.
3. Eva-Marie Meemken, Matin Qaim, Department of Agricultural Economics and Rural Development, Annual Review of Resource Economics 10, 39-63, 2018.
4. A.W De Valença, A Bake, ID Brouwer, KE Giller, Agronomic Biofortification of Crops, Global food security 12, 8-14, 2017.
5. E Bloem, A Albihn, J Elving, L Hermann, L Lehmann, Minna Sarvi, T Schaaf, J Schick, Eila Turtola, Kari Ylivainio Science of the Total Environment 607, 225-242, 2017.
6. Singh, D.P., Prabha, R., Renu, S. et al. Agrowaste bioconversion and microbial fortification have prospects for soil health, crop productivity, and eco-enterprising. Int J Recycl Org Waste Agricult 8 (Suppl 1), 457–472 (2019).
7. RS HARKAL, AV MANWAR, Department of microbiology, DSM College, Impact of Organic Manure, Romanian Journal of Biophysics 32 (1), 2022.
8. Pramod K Pandey, Philip H Kass, Michelle L Soupir, Sagor Biswas, Vijay P Singh, Contamination of water resources by pathogenic bacteria, Amb Express 4, 1-16, 2014.
9. Jian Cui, Jianwei Cui, Jinfeng Li, Wei Wang, Bin Xu, John Yang, Bei Li, Yajun Chang, Xiaojing Liu, Dongrui Yao, improving earthworm quality and complex metal removal from water by adding aquatic plant residues to cattle manure, Journal of Hazardous Materials,2023.
10. Singh, S.K., Barman, M., Sil, A. et al. Nutrient biofortification in wheat: opportunities and challenges. CEREAL RESEARCH COMMUNICATIONS 51, 15–28 (2023).
11. Wickham A, Davis JG. Optimizing Organic Carrot (Daucus carota var. sativus) Yield and Quality Using Fish Emulsions, Cyanobacterial Fertilizer, and Seaweed Extracts. Agronomy. 2023.
12. Sukor A, Qian Y, Davis JG. Organic Nitrogen Fertilizer Selection Influences Water Use Efficiency in Drip-Irrigated Sweet Corn. Agriculture. 2023.

13. Mahmudul Islam Piash, Koki Uemura, Takanori Itoh, Kazunori Iwabuchi, Meat, and bone meal biochar can effectively reduce chemical fertilizer requirements for crop production and impart competitive advantages to the soil, Journal of Environmental Management,2023.
14. Yadav RK, Tripathi MK, Tiwari S, Tripathi N, Asati R, Patel V, Sikarwar RS, Payasi DK. Breeding and Genomic Approaches towards Development of Fusarium Wilt Resistance in Chickpea. Life. 2023.
15. Kumar, K., Shinde, A., Aeron, V. et al. Genetic engineering of plants for phytoremediation: advances and challenges. J. Plant Biochem. Biotechnol. 32, 12–30 (2023).
16. Fang Wang, Yu-Hao Fu, Hong-Jie Sheng, Edward Topp, Xin Jiang, Yong-Guan Zhu, James M. Tiedje, Antibiotic resistance in the soil ecosystem: A One Health perspective, Current Opinion in Environmental Science & Health, Volume 20,2021.

DrillBit

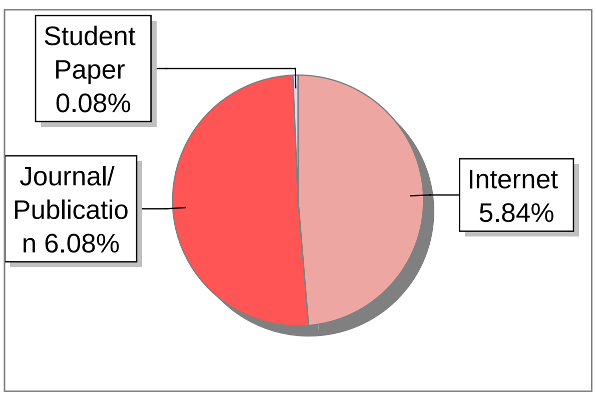
The Report is Generated by DrillBit Plagiarism Detection Software

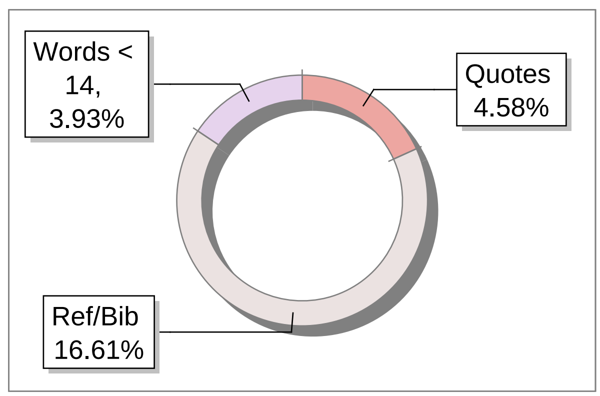
Submission Information

Author Name	Shilpy mam
Title	Paper 1
Paper/Submission ID	1520407
Submitted by	shivani.agr@quantumeducation.in
Submission Date	2024-03-12 11:37:10
Total Pages	35
Document type	Article

Result Information

Similarity **12 %**





Exclude Information

Quotes	Not Excluded
References/Bibliography	Excluded
Sources: Less than 14 Words %	Not Excluded
Excluded Source	**0 %**
Excluded Phrases	Not Excluded

Database Selection

Language	English
Student Papers	Yes
Journals & publishers	Yes
Internet or Web	Yes
Institution Repository	Yes

A Unique QR Code use to View/Download/Share Pdf File

Registrar
Quantum University

DrillBit Similarity Report

12	60	B	A-Satisfactory (0-10%) B-Upgrade (11-40%) C-Poor (41-60%) D-Unacceptable (61-100%)
SIMILARITY %	MATCHED SOURCES	GRADE	

LOCATION	MATCHED DOMAIN	%	SOURCE TYPE
2	www.dx.doi.org	1	Publication
3	www.mdpi.com	1	Internet Data
4	Driver distraction detection using capsule network by Jain-2020	1	Publication
5	Distracted driver detection by combining in-vehicle and image data using deep le by Omerustaoglu-2020	1	Publication
6	www.mdpi.com	1	Internet Data
7	mdpi.com	<1	Internet Data
8	www.researchgate.net	<1	Internet Data
9	mdpi.com	<1	Internet Data
11	www.dx.doi.org	<1	Publication
12	Real-time Detection of Distracted Driving based on Deep Learning by sheng-2018	<1	Publication
13	www.mdpi.com	<1	Internet Data
17	Visual-Manual Distraction Detection Using Driving Performance Indicat, by Li, Zhaojian Bao, - 2017	<1	Publication
20	www.dx.doi.org	<1	Publication

22	Adaptive optimal control based on driving style recognition for plug-in hybrid e by Guo-2019	<1	Publication
23	Auxiliary Demographic Information Assisted Age Estimation With Cascad, by Wan, Jun Tan, Zich- 2018	<1	Publication
26	The impact of task type and pre-task planning condition on the accuracy of inter by Khoram-2019	<1	Publication
27	www.network.bepress.com	<1	Publication
30	Interferometric Wavefront Sensing System Based on Deep Learning by Niu-2020	<1	Publication
31	Software Architecture for Smart Emotion Recognition and Regulation of by Castillo-2016	<1	Publication
32	www.diva-portal.org	<1	Publication
33	www.mdpi.com	<1	Internet Data
37	www.mdpi.com	<1	Internet Data
38	coek.info	<1	Internet Data
40	City energy modelling - Optimising local low carbon transitions with household b by Dias-2019	<1	Publication
42	www.frontiersin.org	<1	Internet Data
43	www.ncbi.nlm.nih.gov	<1	Internet Data
44	moam.info	<1	Internet Data
45	stevemasover.blogspot.com	<1	Internet Data
47	www.freepatentsonline.com	<1	Internet Data
50	ymerdigital.com	<1	Publication

51	Development of controlled heating for fatigue test in overhead conductors at hig by Costa-2020	<1	Publication
53	springeropen.com	<1	Internet Data
56	www.ncbi.nlm.nih.gov	<1	Internet Data
57	arxiv.org	<1	Internet Data
58	Differential Surface Expression and Phosphorylation of the N-Methyl-D-aspartate by Hall-1997	<1	Publication
59	github.com	<1	Internet Data
60	omicsonline.org	<1	Internet Data
61	bioinform.jmir.org	<1	Internet Data
62	biomedcentral.com	<1	Internet Data
63	blog.ipleaders.in	<1	Internet Data
64	docplayer.net	<1	Internet Data
65	link.springer.com	<1	Internet Data
67	www.dx.doi.org	<1	Publication
69	www.dx.doi.org	<1	Publication
73	1library.co	<1	Internet Data
74	academic.oup.com	<1	Internet Data
75	actapress.com	<1	Internet Data
76	citeseerx.ist.psu.edu	<1	Internet Data

77	Civic integration or ethnic segregation Models of ethnic and civic nationalism by Duerr-2016	<1	Publication
78	cloudfront.escholarship.org	<1	Internet Data
80	dochero.tips	<1	Internet Data
83	moam.info	<1	Internet Data
84	publications.iowa.gov	<1	Publication
85	springeropen.com	<1	Internet Data
86	Submitted to Visvesvaraya Technological University, Belagavi	<1	Student Paper
87	The Association of ASA Class on Total Knee and Total Hip Arthroplasty, by Schaeffer, Jordan F- 2015	<1	Publication
88	www.doaj.org	<1	Publication
89	www.isihome.ir	<1	Publication
90	ACM Press the 7th international conference- Salzburg, Austria (200, by Heffelaar, Tobias - 2005	<1	Publication
91	IEEE 2018 IEEE Latin American Conference on Computational Intellige, by da Silva Oliveira, - 2018	<1	Publication

Registrar
Quantum University

A Comprehensive Review on Machine Learning Techniques for Reckless Driving Detection

Shilpy Sharma[1], Dr. Manish Sharma[1], Dr. Rashmi Sharma[2]
shilpy.cse@quantumeducation.in, director@quantumeducation.in, rashminonumanu@gmail.com
[1]Quantum University, Roorkee, [2]AKGEC Ghaziabad

Abstract: ***With increased concerns over road safety and the incidence of reckless driving events, there is a greater demand for smart systems that identify and mitigate harmful driving behaviours. This study provides a detailed overview of machine learning approaches used in the field of reckless driving identification. The primary goal is to investigate the different approaches, algorithms, and models used for identifying patterns suggestive of potentially dangerous driving behaviour. The study comprises a detailed review of current research, showing significant advances in machine learning applications for reckless driving identification. A taxonomy of the various methodologies is offered, with classifications based on feature extraction, model topologies, and data sources. The review examines the constraints and limits of each approach, offering insights into potential areas for improvement and future research possibilities.***

Keywords: ***Data systems, autonomous cars, distraction detection, driver distraction, driver monitoring, driving distraction, intelligent transportation***

Introduction:

Existing monitoring systems may be divided into two categories: sleepiness detection systems and distraction detection systems. However, the distinction between them is not evident because cognitive distraction might be connected to the driver's alertness in some circumstances (e.g., daydreaming). They both have an effect on the driver's physiological condition by decreasing awareness and consequently increasing reaction time. Electronics for driver assistance are found in abundance in modern automobiles (multimedia displays, navigation, temperature control, parking radar, etc.). Additionally, third-party entertainment gadgets like music players, PDAs, cell phones, etc. are diverting an increasing amount of the driver's attention, which is leading to an increase in traffic incidents and even accidents. 1.35 million fatalities attributed to traffic accidents were reported in 2018, according to the World Health Organization (WHO). Each year, traffic accidents damage almost 50 million people worldwide. As a result, in recent years, human safety while driving has become a major socioeconomic problem on a global scale. When a driver's attention wanders while they are driving, that is, when they are thinking about something other than the task of driving, it is known as a cognitive distraction. Distractions brought on by inattention, tiredness, or exhaustion include visual distractions. It most frequently refers to situations where drivers are using multimedia devices, such as navigation or entertainment systems and cell phones, which "salient visual information away from the road causing involuntary off-road eye glances and momentary rotation of the head. Olfactory distraction happens when an offensive or overpowering smell from the roadside disturbs the motorist. Gustatory distraction typically occurs if the motorist coughs as a result of the food's bitter or spicy flavor. It should be mentioned that gustatory distractions (a type of physical distraction) frequently occur after meals. Drivers may get cognitively, visually, or mechanically distracted as a result of these circumstances.

Literature Review: Driver distraction is detected by collecting photos using a camera mounted in front of the driver or within the automobile. The recorded photos are submitted for categorization in order to detect driving behaviours. Drivers are distracted in a variety of ways, as previously stated. Eating and drinking while driving, conversing with fellow passengers, using in-vehicle electronic gadgets ,watching roadside digital billboards/advertising/logo signs and using a mobile phone to contact or text are all popular distractions. Developing a system that can monitor distractions is an effective strategy to combat distracted driving. These strategies alter the in-vehicle information-system functionality based on the driver's condition. Correctly detecting the driver's status is critical in these systems. Some paper reviews in the form of their methodology, analysis, result and findings are mentioned in below table.

SNO	TITLE	AUTHOR	NAME OF JOURNAL	FINDING ANALYSIS AND RESULT	RESEARCH GAP
1	Artificial intelligence system for driver distraction by stacked deep learning classification	Qibtiah, Raja Mariatul, Zalhan Mohd Zin, and Mohd Fadzil Abu Hassan.	Bulletin of Electrical Engineering and Informatics 12.1 (2023): 365-372.	The technique employed stacked CNN features and overlapped HAAR to classify eye regions as either open or closed. This method continuously compares with adaptable thresholds to limit the effects of distraction while taking into consideration existing intelligent transportation system-based solutions.Accurate driving datasets are used to analyse the experimental outcomes. Over 80% accuracy was achieved in 456 iterations, with almost no loss.	Additional research into different methods and FCW could offer further data to support the proposed approach.
2	Real-time driver distraction recognition: A hybrid genetic deep network based approach	Aliohani,A beer	*Alexandria Engineering Journal* 66 (2023): 377-389.	First, it selected the feature extractor's structure using genetic algorithms, selecting from well-known CNN models including VGG19, ResNet50, and DenseNet121. The State Farm dataset, which includes data on one safe driving course and nine risky behaviours like texting and driving, conversing with passengers, drinking, and so on, was used to develop the model.	MLP Mixer and Check on its performance for driver distraction classification can be evaluated. The proposed model can be evaluated on a new set of datasets, especially from a different angle of drivers. Also,more diverse commands can be added to the

				According to experimental data, a combination of deep neural networks and genetic algorithms can classify distracted drivers on state farms with 99.80% accuracy.	already available driver command recognition dataset.
3	Driver distraction detection via multi-scale domain adaptation network	Wang,jing and Zhongchang Wu	*IET Intelligent Transport Systems* (2023).	The purpose of this work is to enhance the generalisation capacity of models of distracted driving that are influenced by several elements, including the driver, the environment, the angle of observation, and more. First, a new backbone was constructed using multi-scale convolution, which better accommodated the target's valuable features at various sizes. Second, the domain adaptation network was created by the authors with the goal of using adversarial training to increase the model's adaptability to different data sources. Ultimately, dropout is incorporated into the fully connected layer to improve the model's capacity for generalisation. With an accuracy improvement in the cross-driver and cross-dataset experiments, the comparison results on the extensive driver distraction detection dataset demonstrate the authors' method's ability to effectively detect driver distraction and high generalisation performance.	Driver distraction detection models on videos and real-time camera data to capture more spatiotemporal features to improve the accuracy of driver distraction detection could be implemented. Model can be deployed on embedded devices and further study the lightweight model with high precision and low latency to meet the needs of real-time monitoring on the terminal platform.
4	Deepsegmenter: Temporal action localization for	Aboah, Armstrong, et al	*arXiv preprint arXiv:2304.08261*	The Data Module, Activity Segmentation Module, Classification Module, and Postprocessing Module are the four main modules that make up the suggested structure.	The study may lack an in-depth sensitivity analysis of the proposed framework's performance

	detecting anomalies in untrimmed naturalistic driving videos			The suggested system's effectiveness, efficiency, and resilience are demonstrated by the experimental findings.	concerning different parameters or variations in the input data. A more comprehensive examination of the framework's robustness and adaptability to diverse scenarios could help identify areas for improvement.
5	Distracted driving detection based on the fusion of deep learning and causal reasoning.	Ping, Peng, et al.	*Information Fusion* 89 (2023): 121-142.	Based on the causal And-or graph (C-AOG) and temporal-spatial double-line DL network (TSD-DLN), the authors present a method for recognising distracted behaviour. To identify the distracted driving posture, TSD-DLN combines the spatial characteristic of a single video frame with the attention feature acquired from the dynamic optical flow information. The suggested method performs much better than other SOTA algorithms while processing consecutive frames to acquire distracted driving behaviour, as demonstrated by the experimental findings.	The findings may not include the user-centric features of the distracted driving behaviour identification system. There is a research gap in determining how well the system fits with user demands, preferences, and usability concerns, all of which are crucial for effective adoption and integration in real-world circumstances.
6	Driver Drowsiness Monitoring System Using Visual behaviour And Machine Learning	Jayantha, gummula, and p. Velayutham.	*Journal of Engineering Sciences* 14.01 (2023).	This work develops a real-time, low-cost system for detecting driver drowsiness with a reasonable level of accuracy. The developed system employs a camera to record the video and image processing algorithms to determine the driver's face in each frame. It has proven possible to attain 100% specificity and 95.58%	The system can be implemented in hardware to make it portable for car system and pilot study on drivers can be carried out to validate the developed system. Also,work can be carried out to implement them in the developed system to do the classification (i.e.,

				sensitivity in support vector machine-based classification.	drowsiness detection) online.
7	4D: a real-time driver drowsiness detector using deep learning	Jahan, Israt, et al	*Electronics* 12.1 (2023): 235.	In order to better assess a driver's level of tiredness, this study outlines how to build a comprehensive drowsiness detection system that can anticipate the driver's eye condition and warn them before there are significant risks to road safety. The 4D model performed exceptionally well (about 97.53% accuracy for predicting the eye condition in the test dataset) when trained using training samples from the same dataset. Two more pretrained models (VGG16, VGG19) performed worse than the 4D model.	There could be a major discrepancy between the driving-behavior-based measurements used in real-world driving and those used in simulations. Devices that monitor a patient's heart rate to determine if they are qualified to operate a vehicle could be implemented.
8	Synthetic distracted driving (syndd1) dataset for analyzing distracted behaviors and various gaze zones of a driver	Rahman, Mohammed Shaiqur, et al.	*Data in brief* 46 (2023): 108793.	The purpose of this paper is to provide machine learning models with a dataset of synthetic distracted driving (SynDD1) so they can identify and evaluate the various distracted driving behaviours and gaze zones of drivers.	According to the approach, participants execute distracting tasks constantly for a brief period of time. A research gap may exist in understanding how varying durations of distracting activities affect gaze patterns and distraction recognition. Variability in time intervals may increase the dataset's applicability to a larger set of circumstances.
9	Advanced Driver Fatigue	Parvez M, Muzammil, et al	*Engineering Proceedings*	This research presents a noncontact method of using a detecting methodology to	Using an infrared camera could have helped in increased

	Detection by Integration of OpenCV DNN Module and Deep Learning		34.1 (2023): 15.	ascertain a driver's level of fatigue. The system has a 96.8% accuracy rate.	detection in low-light conditions. Furthermore, a multi-model machine-learning strategy could have been used. To improve performance extra modalities like audio channels with video frames could have been inserted.
10	System and method for driver drowsiness detection using behavioral and sensor-based physiological measures	Bajaj, Jaspreet Singh, et al	*Sensors* 23.3 (2023): 1292.	The proposed hybrid model makes use of the Galvanic Skin Response (GSR) sensor as a physiological measure to gather the driver's skin conductance, which helps to improve overall accuracy, and AI-based Multi-Task Cascaded Convolutional Neural Networks (MTCNN) as a behavioural measure to recognise the driver's facial features. The effectiveness of the model has been calculated in a virtual setting. The results demonstrate that the suggested hybrid model has an efficacy of 91% in recognising the driver's transition from an awake to drowsy state under all circumstances.	Adding more sensors, including the PPG, pulse rate sensor, and IR-UWB radar, might enhance the suggested model's effectiveness. Advanced deep-learning approaches could enable real-time detection of driver sleepiness.
11	Understanding the drowsy driving crash patterns from correspondence regression analysis	Rahman, M. Ashifur, Subasish Das, and Xiaoduan Sun.	*Journal of safety research* 84 (2023): 167-181.	The primary collective correlations of features in crashes related to drowsy driving were identified in this study using 5-year (2015–2019) crash data and the correspondence regression analysis approach. Interpretable patterns based on injury levels were also identified. Findings: Crash clusters were used to detect a number of	Research could focus on identifying unique risk factors and patterns in these distinct settings to inform tailored interventions. Understanding how drivers respond to and benefit from advisory technologies can

				sleepy driving-related crash patterns, including: pickup truck crashes in manufacturing/industrial areas; late-night crashes in business and residential districts; heavy truck crashes on elevated curves; afternoon fatigue crashes by middle-aged female drivers on urban multilane curves; crossover crashes by young drivers on low-speed roadways; crashes by male drivers during dark, rainy conditions.	contribute to the refinement of these tools for enhanced safety.
12	How to Prevent Drivers before Their Sleepiness Using Deep Learning-Based Approach	Akrout, Belhassen, and Sana Fakhfakh.	*Electronics* 12.4 (2023): 965.	A transfer learning step by the MobileNetV3 model is performed on the normalized images to extract more descriptors from the driver's eyes	integration of multiple sensors beyond infrared cameras, such as LiDAR, radar, or advanced imaging techniques, to create a robust and comprehensive system could be implemented. methods for real-time adaptation to changing light conditions could be implemented.
13	Network Analysis of Facial Behaviours for Non-Contact Driver Distraction Detection	Bahmani, Zahra	*papers.ssrn.com*	The accuracy of the suggested technique in differentiating between distracted and normal driving was 60.96%. The findings indicate that one helpful characteristic to differentiate between distracted driving and regular driving was the variation in the interactions between the sources and sinks.	Generalization to various traffic conditions, driving environments, and individual driver characteristics could have been explored to ensure the robustness of the proposed method.
14	ADABase: A Multimodal Dataset for	Oppelt, Maximilian P., et al.	*Sensors* 23.1 (2023): 340.	Inspired by real-world semi-autonomous vehicles, the author developed the ADABase (Autonomous Driving Cognitive Load Assessment Database) as a	specificity of cognitive load effect corresponding to different task types could have been

	Cognitive Load Estimation			reference technique to induce cognitive load onto participants. We also used the well-established n-back test in addition to our unique simulator-based k-drive test.	investigated. Generalizability of the fIndings across diverse demographic groups could have been examined.
15	Young Novice Drivers' Cognitive Distraction Detection: Comparing Support Vector Machines and Random Forest Model of Vehicle Control Behavior.	Xue, Qingwan, et al.	*Sensors* 23.3 (2023): 1345	This paper conducted a driving simulator experiment to better understand the relationship between drivers' cognitive distractions and traffic safety, as well as to better analyse the mechanism underlying young drivers' driving distractions.	Integrating data from multiple modalities such as heart physiology, eye movements and potentially additional sensor data, to enhance the discrimination model's accuracy could have been incorporated using advanced machine learning techniques.
16	Learning naturalistic driving environment with statistical realism.	Xintao Yan Zhengxia Zou Shuo Feng ,Haojie Zhu , Haowei Sun & Henry X. Liu	https://doi.org/10.1038/s41467-023-37677-5	The authors of this paper proposed a safety mapping network and a conflict critic model to improve the process of generating safety-critical events by modelling real-world frequencies and patterns. NeuralNDE is a deep learning-based framework that learns multi-agent interaction behaviour from vehicle trajectory data.	The article does not provide a comparison with existing high-fidelity simulation settings for AV testing. Benchmarking against established simulators will help you better grasp the proposed approach's improvements and limits.
17	Detection of Driver Cognitive	A. Misra, S. Samuel, S. Cao and K. Shariat madari	IEEE Access, vol. 11, pp. 18000-18012, 2023, doi: 10.1109/ACC	In this study, the author analysed data from a driving simulator study involving 40 drivers in a variety of driving scenarios to identify features	The research study acknowledges that because it was carried out in an academic

	Distraction Using Machine Learning Methods		ESS.2023.3245122.	from various sources, such as eye tracking, physiological, and vehicle kinematics data, that are relevant towards the classification of distracted and non-distracted drivers.	atmosphere, the sample was not entirely randomised. This restriction might be overcome in future studies by using a more randomised and diversified sample, which might include people from different backgrounds, driving experiences, and demographic groups. This would increase the findings' external validity and increase their applicability to a larger population.
18	Identification of dangerous driving state based on lightweight deep learning model	Wei Song , Guangde Zhang , Yicheng Long	*Identification of dangerous driving state based on lightweight deep learning model, Computers and Electrical Engineering, Volume 105, 2023, 108509, ISSN 0045-7906, https://doi.org/10.1016/j.compeleceng.2022.108509.*	The popular deep learning image classification models, such as SqueezeNet, MobileNetV1, MobileNetV2, ShuffleNetV1, AlexNet, and VGG16, are constructed in this study for comparison studies.	The analysis of the weight distribution and feature extraction procedure is mentioned in the study, however interpretability and explainability need to be given more attention. Gaining confidence and acceptance in practical applications requires an understanding of the model's classification process, particularly in essential jobs like driving while intoxicated.

19	Risk-aware controller for autonomous vehicles using model-based collision prediction and reinforcement learning	Eduardo Candela, Olivier Doustaly, Leandro Parada, Felix Feng, Yiannis Demiris, Panagiotis Angeloudis	Artificial Intelligence, Volume 320, 2023, 103923, ISSN 0004-3702, https://doi.org/10.1016/j.artint.2023.103923	In this paper, a novel risk-aware framework based on Reinforcement Learning (RL) and a customised collision prediction model is presented for training autonomous vehicles (AVs). The RL state vector is produced by the collision prediction model, which is based on Gaussian Processes and vehicle dynamics.	The short-term decrease in collision rates is the primary concern of the paper. The long-term safety implications of the suggested framework might be investigated, including how well the AV agents sustain safety levels over time and whether learning stability and model deterioration are causes for worry.
20	A deep learning-based distracted driving detection solution implemented on embedded system	Sahoo, G.K., Das, S.K. & Singh, P	*Applied Soft Computing, Volume 96, 2020, 106657, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2020.106657.*	Ten distracted driving postures are classified using the transfer learning SqueezeNet 1.1 implementation with the last layer update in this research. The system's training performance achieves 99.93% classification accuracy and good driving posture estimate. The AWS cloud platform is used for training, and a Raspberry Pi 4B is equipped with the best model for testing exclusively in stationary vehicles. The deep learning model is constructed with Pytorch and Python, and comparative analysis shows that the SqueezeNet model outperforms the other models.	Ten predetermined distracted driving postures are the focus of the study. Subsequent investigations may examine the model's ability to detect novel or unexpected distracted behaviours in real time, thereby guaranteeing flexibility in response to evolving road safety issues. Although the study places a strong emphasis on performance measures, revealing the model's decision-making process—particularly in high-stress scenarios—would increase the system's credibility. Understanding the

					behaviour of the model may be aided by including interpretability strategies.
21	Driving Decisions for Autonomous Vehicles in Intersection Environments: Deep Reinforcement Learning Approaches with Risk Assessment	Wangpengfei Yu,Yubin Qian ,Jiejie Xu,Hongtao Sun and Junxiang Wang	*World Electric Vehicle Journal* 14, no. 4: 79. https://doi.org/10.3390/wevj14040079	In this study, a non-deterministic vehicle driving risk assessment method is proposed for intersection scenarios and introduced into a learning-based intelligent driving decision algorithm. In addition, this study proposes an attention network based on state information. In this study, a typical intersection scenario was constructed using simulation software, and experiments were conducted.	The study focuses mostly on simulation-based investigations. Extending the assessment of the proposed algorithm to real-world driving scenarios is critical for determining its practical usefulness, especially given the inherent complexity and unpredictability found on actual highways.
22	A Proactive Recognition System for Detecting Commercial Vehicle Driver's Distracted Behavior	Yan, Xintong, Jie He, Guanhe Wu, Changjian Zhang, and Chenwei Wang	*Sensors* 22, no. 6: 2373. https://doi.org/10.3390/s22062373	In this Five CNN sub-models were established for different posture categories and to improve the efficiency of recognition, accompanied by a holistic multi-cascaded CNN framework.	Although the paper compares cascaded and non-cascaded CNN models, assessing different kinds of driver monitoring systems may represent a research gap. Subsequent research endeavours may investigate the efficacy of alternative algorithms or technologies outside CNN models, furnishing a more all-encompassing comprehension of their advantages and drawbacks.

23	IoT-Enabled Driver Drowsiness Detection Using Machine Learning	M. Guria and B. Bhowmik,	International Conference on Parallel, Distributed and Grid Computing (PDGC)	This paper develops an intelligent alerting method to prevent accidents caused by drivers falling asleep at the wheel. The proposed approach detects drowsiness in analyzing the live streaming of drivers' videos. Eye Aspect Ratio (EAR) and the Euclidean distance of the eye are used to analyze the input video stream to identify sleepy drivers	As the paper primarily focuses on the technical features of the alerting mechanism, it is important to understand how drivers accept such systems. Users' opinions, attitudes, and degrees of acceptance regarding the integration of sleepiness detection systems into their cars should all be investigated in research. Investigating false positives and negatives is also necessary to reduce any interruptions or miss important circumstances.
24	Modeling Urban Freeway Rear-End Collision Risk Using Machine Learning Algorithms	Xiaolong Ma ,Qiang Yu and Jianbei Liu	*Sustainability* 14, no. 19: 12047. https://doi.org/10.3390/su141912047	In this study a new framework was proposed to develop the rear-end collision probability (RCP) model between two vehicles based on Generalized Pareto Distribution (GPD). The freeway rear-end collision risk (F-RCR) was defined as the sum of the rear-end collision probability of each vehicle and divided into three levels which was high, median, and low rear-end collision risk.	The determination of a highly imbalanced dataset (high F-RCR accounting for around 10%) indicates a need for further research on how sensitive machine learning classification algorithms are to these kinds of imbalances. In the context of F-RCR prediction, future research should examine methods and approaches to raise the predicted accuracy of

					machine learning models when working with unbalanced datasets.
25	Deriving Driver Behavioral Pattern Analysis and Performance Using Neural Network Approaches	Meenakshi Malik , Rainu Nandal, Surjeet Dalal , Vivek Jalglan and Dac-Nhuong Le	*Intelligent Automation & Soft Computing* 32, no. 1 (2022).	In this study, neural network algorithms were utilized in order to conduct an intensive study to determine and analyze the prevailing driver behavior and driving styles. This proposed approach evaluated multiple factors that were determinants in identifying specific driver behavior and driving styles	The focus of the research is primarily on data-driven parameters, including acceleration, braking circumstances, and steering wheel angle. Future studies could focus more on understanding the psychological and human factors—such as stress levels, attention spans, and emotional states—that affect driver behaviour.
26	Safety monitoring system of personal mobility driving using deep learning	Eunji Kim, Hanyoung Ryu, Hyunji Oh, Namwoo Kang	*Journal of Computational Design and Engineering, Volume 9, Issue 4, August 2022, Pages 1397–1409, https://doi.org/10.1093/jcde/qwac061*	This study proposes a deep learning-based personal mobility driver monitoring system that detects inattentive driving by classifying vibration data transmitted to the e-scooter when the driver fails to concentrate on driving. First, the N-back task technique is used. The driver was stimulated by external visual and auditory factors to generate a cognitive load, and vibration data were collected through a six-axis sensor. Second, the generated vibration data were pre-processed using short-time Fourier transform and wavelet transform (WT) and then converted into an image (spectrogram).Experimental results show that multimodal	The study states that the lack of data led to the creation of individual models. In order to improve model generalisation, future research should concentrate on expanding the dataset size. Additionally, it would be beneficial to investigate the feasibility of creating a more comprehensive model that can integrate a variety of driving styles into a single framework.

				DenseNet121 with WT can accurately classify safe, slightly anxious, and very anxious driving conditions. The proposed model can be applied to real-time monitoring and warning systems for sharing service providers and used as a basis for insurance and legal action in the case of accidents.	
27	COOPERNAUT: End-to-End Driving with Cooperative Perception for Networked Vehicles	Jiaxun Cui, Hang Qiu, Dian Chen, Peter Stone, Yuke Zhu;	Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 17252-17262	This model encodes LiDAR information into compact point-based representations that can be transmitted as messages between vehicles via realistic wireless channels. To evaluate our model, we develop AutoCastSim, a network-augmented driving simulation framework with example accident-prone scenarios.	Exploring the use of various sensor modalities (such as radar, lidar, and cameras) to enhance perceptual abilities and lessen the effects of individual sensor constraints. The goal of research could be to create fusion algorithms—which efficiently integrate data from several sensors—that will improve the overall accuracy and dependability of perception.
28	HSDDD: A Hybrid Scheme for the Detection of Distracted Driving through Fusion of Deep Learning and Handcrafted Features	Alkinani, Monagi H., Wazir Zada Khan, Quratulain Arshad, and Mudassar Raza	Sensors 22 doi: 10.1109/ACCESS.2021.313813	HSDDD is based on three-tiered architecture. The three tiers are named as Coordination tier, Concatenation tier and Classification tier. Cubic SVM has shown the performance accuracy of 95.1%	SVM and KNN are two common machine learning classifiers mentioned in the research for the final classification. Researchers could investigate novel computer paradigms like brain-like computing or quantum computing to improve accuracy and open up new avenues. These cutting-edge

					methods could provide fresh perspectives on feature extraction, fusion, and classification, thus increasing the precision with which distracted driving is detected.
29	Distracted Driver Detection Based on a CNN With Decreasing Filter Size	B. Qin, J. Qian, Y. Xin, B. Liu and Y. Dong	Journal of Ambient Intelligence and Humanized Computing 12, no. 1 (2021): 193-200.	Author proposed a new D-HCNN model based on a decreasing filter size with only 0.76M parameters, a much smaller number of parameters than that used by models in many other studies. D-HCNN uses HOG feature images, L2 weight regularization, dropout and batch normalization to improve the performance.and conduct experimental evaluations on two public datasets, AUC Distracted Driver (AUCD2) and State Farm Distracted Driver Detection (SFD3). The accuracy on AUCD2 and SFD3 is 95.59% and 99.87%, respectively, higher than the accuracy achieved by many other state-of-the-art methods.	Enhancing the D-HCNN model's interpretability and explainability could be the goal of future research to help users comprehend how and why particular judgements are made. This is especially crucial in safety-critical applications where trust and openness are essential, such as the detection of inattentive driving.
30	Design of an Efficient Distracted Driver Detection System: Deep Learning Approaches	N. K. Vaegae, K. K. Pulluri, K. Bagadi and O. O. Oyerinde	*IEEE Access*, vol. 10, pp. 116087-116097, 2022, doi: 10.1109/ACCESS.2022.3218711.	The proposed DDDS scheme contains the pre-processing module, image augmentation techniques, and two classification modules based on deep learning architectures.Accuracy of 86.1% and 87.92% are achieved with VGG-16 and ResNet-50 models, respectively, and it is observed that the DDDS scheme is found highly efficient for c4, c5, and c7 categories of the State-Farm dataset.	In accordance with the research, adding temporal context could improve model accuracy and reduce classification errors. In order to capture dynamic changes in driver behaviour and improve the model's accuracy in detecting distractions, future study could investigate the

					incorporation of temporal information, such as video sequences or tracking across time.
31	E2DR: A Deep Learning Ensemble-Based Driver Distraction Detection with Recommendations Model	Aljasim, Mustafa, and Rasha Kashef	*Sensors* 22, no. 5: 1858. https://doi.org/10.3390/s22051858	This paper proposes E2DR, a new scalable model that uses stacking ensemble methods to combine two or more deep learning models to improve accuracy, enhance generalization, and reduce overfitting, with real-time recommendations. The highest performing E2DR variant, which included the ResNet50 and VGG16 models, achieved a test accuracy of 92% as applied to state-of-the-art datasets, including the State Farm Distracted Drivers dataset, using novel data splitting strategies.	The research highlights the model's potential to offer suggestions for guaranteeing the driver's and others' safety and well-being. Future research can concentrate on improving the suggestion system, taking into account tailored interventions depending on the particular setting and degree of distractions, and combining with in-car technologies to provide support and notifications in a timely manner.
32	Innovative Framework for Distracted-Driving Alert System Based on Deep Learning	P. -W. Lin and C. -M. Hsu	*IEEE Access*, vol. 10, pp. 77523-77536, 2022, doi: 10.1109/ACCESS.2022.3186674	Author proposed a novel framework herein that combines driving perception and driver behavior recognition to provide the driver with appropriate warnings	Although it is known that weather conditions have a significant impact on driving safety, the system does not take this into account at this time. In the future, the model should be expanded to incorporate weather-related variables, including rain, snow, or slippery roads, as they might have a big impact on

					driving dynamics and accident probability.
33	A Machine Learning Framework for Automated Accident Detection Based on Multimodal Sensors in Cars	Hozhabr Pour H, Li F, Wegmeth L, Trense C, Doniec R, Grzegorzek M, Wismüller R	*Sensors* 22, no. 10: 3634. https://doi.org/10.3390/s22103634.	Author proposed a ML framework for automated car accident detection based on mutimodal in-car sensors.The main observations of this study are as follows: (1) CNN features with a SVM classifier obtain very promising results, outperforming all other tested approaches. (2) Feature engineering and feature learning approaches were finding different best performing features. Therefore, our fusion experiment indicates that these two feature sets can be efficiently combined. (3) Unsupervised feature extraction remarkably achieves a notable performance score.	The research emphasises how autoencoders (AE), in particular, exhibit promising performance in unsupervised deep feature learning. Future research should examine different approaches and architectures for unsupervised feature learning in order to improve the model's capacity to extract significant features from the input data. More reliable accident detection models may result from this.
34	A Data Augmentation Approach to Distracted Driving Detection	Wang, Jing, ZhongCheng Wu, Fang Li, and Jun Zhang	*Future Internet* 13, no. 1: 1. https://doi.org/10.3390/fi13010001	This paper proposes a data augmentation method for distracted driving detection based on the driving operation area.The classification result achieves a 96.97% accuracy using the distracted driving dataset. The results show the necessity of driving operation area extraction in the preprocessing stage, which can effectively remove the redundant information in the images to get a higher classification accuracy rate.	Several categories are used by the present classification method to group unsafe driving behaviours. However, the study implies that several risky behaviours might coexist in real-world driving scenarios. Future studies should examine strategies for dealing with the co-occurrence of several risky behaviours, taking into account the complexity of

					actual driving situations. This could entail adding models that can manage several concurrent behaviours or improving the classification strategy.
35	An efficient traffic incident detection and classification framework by leveraging the efficacy of model stacking	Zafar Iqbal ,Majid I. Khan, Shahid Hussain, and Asad Habib	Hindawi Complexity Volume 2021, Article ID 5543698, 17 pages https://doi.org/10.1155/2021/5543698	This study proposed an efficient incident detection and classification (E-IDC) framework for smart cities, by incorporating the efficacy of model stacking, to classify the incidents with respect to their types and severity levels.	Misclassification can be a problem for context-aware AID systems, which categorise particular kinds of occurrences. This is particularly true when handling a variety of incident circumstances. Subsequent studies ought to explore techniques for augmenting the resilience of context-aware systems, mitigating the possibility of misclassifications and enhancing the precision of incident classification. This could entail creating more complex algorithms or hybrid methods that classify data based on a variety of parameters.
36	Robust deep learning-based driver distraction	A. Ezzouhri, Z. Charouh, M. Ghogho and Z. Guennoun	*IEEE Access*, vol. 9, pp. 168080-168092, 2021, doi: 10.1109/ACC	The suggested technique involves segmenting the driver's bodily parts using deep learning before detecting and classifying distractions. Experiments demonstrate that the segmentation module	While this research concentrates on CNN-based classification and image segmentation, multimodal

	detection and classification		ESS.2021.3133797	significantly increases classification performance. The proposed approach has an average accuracy of more than 96% on the author's dataset and 95% on the public AUC dataset.	information integration may be investigated in other studies. Adding visual data to other sensor inputs—like audio or physiological signals—may help to increase overall detection accuracy and offer a more thorough picture of driver distraction.
37	Driver Distraction Detection Methods: A Literature Review and Framework	A. Kashevnik, R. Shchedrin, C. Kaiser and A. Stocker	*IEEE Access*, vol. 9, pp. 60063-60076, 2021, doi: 10.1109/ACCESS.2021.3073599.	This framework visualizes the whole detection information chain from used sensors, measured data, computed data, computed events, inferred behavior, and inferred distraction type.	While the report offers a technical overview, user-centric techniques and human factors research could be incorporated in subsequent studies. Design and user acceptability can be enhanced by having a better understanding of how drivers view and react to distraction detection systems. Furthermore, taking individual variances in cognitive load and driver behaviour into account can improve the framework's flexibility.
38	CNN Based Driver Drowsiness Detectio	H. Varun Chand and J. Karthikeyan	Intelligent Automation & Soft Computing DOI:10.3260	This paper proposes a novel model of multi-level distribution of detecting the driver drowsiness using the Convolution Neural Networks	While the study indicated that it can shorten the time it takes to detect distractions, a more thorough

	n System Using Emotion Analysis		4/iasc.2022.020008	(CNN) followed by the emotion analysis.	examination of real-time performance indicators is required. With the time needed for data collection, processing, and decision-making taken into account, research should concentrate on determining the latency of the suggested model in practical settings. This is critical for applications where prompt detection is required.
39	Driving Behaviour Analysis Using Machine and Deep Learning Methods for Continuous Streams of Vehicular Data	Peppes N, Alexakis T, Adamopoulou E, Demestichas K.	*Sensors* **2021**, *21*, 4704. https://doi.org/10.3390/s21144704	This paper proposes and presents a novel approach for continuous data gathering, storage and analysis based on state-of-the-art streaming processes as well as big data and machine and deep learning technologies	While the study recommends using complex event processing (CEP) and semantic technologies to learn more about driving behaviour and road circumstances, a thorough investigation of how these technologies can be successfully incorporated into the current platform is still necessary. Data interoperability, real-world implementation issues, and the benefits of combining sensor data with outside information sources should all be the main areas of study.

40	Driving Style Recognition System Using Smartphone Sensors Based on Fuzzy Logic	Nidhi Kalra, Raman Kumar Goyal , Anshu Parashar , Jaskirat Singh and Gagan Singla	*Computers, Materials & Continua* 69, no. 2 (2021). DOI:10.32604/cmc.2021.018732	In this A driving style recognition system based on fuzzy logic is designed to classify different driving styles and control reckless driving by taking the longitudinal/lateral acceleration and speed as input parameters	The study focuses on accelerometer and GPS sensors, other smartphone sensors like a gyroscope, magnetometer, or camera may also be integrated in the future.. Future studies should focus on the creation and assessment of virtual reorientation methods, taking into account the difficulties in preserving precision and consistency in identifying driving events in various orientations.
41	Drive-Awake: A YOLOv3 Machine Vision Inference Approach of Eyes Closure for Drowsy Driving Detection	J. R. Macalisang, A. S. Alon, M. F. Jardiniano, D. C. P. Evangelista , J. C. Castro and M. L. Tria	IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET), Kota Kinabalu, Malaysia, 2021, pp. 1-5, doi: 10.1109/IICAIET51634.2021.9573811.	The suggested model has a wide range of possible applications, including human-computer interface design, facial expression detection, and determining driver tiredness and drowsiness. The YOLOv3 algorithm, as well as additional tools like Pascal VOC and Labelling, were used to build this approach, which collects and trains a driver dataset that feels drowsy.	Convolutional neural networks (CNNs), in particular, are popularly referred to as "black-box" deep learning models. Future studies should concentrate on techniques to improve the model's decision-making process's interpretability and explainability, particularly in safety-critical applications like the identification of driver drowsiness.
42	Optimally-	Koay, Hong Vin,	*Sensors* 21, no. 14: 4837.	This work introduced an ensemble of ResNets, which is	In subsequent studies, several pre-

	Weighted Image-Pose Approach (OWIPA) for Distracted Driver Detection and Classification	Joon Huang Chuah, Chee-Onn Chow, Yang-Lang Chang, and Bhuvendhraa Rudrusamy	https://doi.org/10.3390/s21144837	named Optimally-weighted Image-Pose Approach (OWIPA), to classify the distraction through original and pose estimation images. The pose estimation images are generated from HRNet and ResNet.he experimental results show that the proposed approach achieves 94.28% accuracy on AUC Distracted Driver Dataset.	trained models, including VGG, Inception, or EfficientNet, might be tested and their effectiveness assessed using the suggested methods. Prospective studies may concentrate on creating models that take into account the temporal dynamics of distractions over an extended period of time.
43	Driver distraction detection using capsule network	Jain, Deepak Kumar, Rachna Jain, Xiangyuan Lan, Yash Upadhyay, and Anuj Thareja	*Neural Computing and Applications* 33 (2021): 6183-6196.	Author proposed a CapsNet-based approach for detecting the distracted driver which is a novel approach. The proposed method scores perform well on the real-world environment inputs when compared to other famous methods used for the same.The proposed methods get high scores for all the most commonly used metrics for classification. On the testing set, the proposed method gets an accuracy of 0.90, 0.92 as precision score, 0.90 as recall score and 0.91 as F-measure.	While typical convolutional neural networks are more interpretable than capsule networks, which are known for their ability to capture hierarchical features, the latter are frequently criticised for their inferior interpretability. In order to get insight into the model's decision-making process, future research could investigate ways to improve CapsNets' explainability in the context of distracted driver detection.
44	Distracted driving recognition method based on	Rao, Xuli, Feng Lin, Zhide Chen, and Jiaxu Zhao	*Journal of Ambient Intelligence and Humanized Computing*	This method uses the PCA technology to whiten the driving image, which reduces the redundancy and correlation of the pixel matrix. The results of experimental analysis show	Despite reporting a high accuracy of 97.31%, the research does not cover other important

	deep convolutional neural network			that the accuracy of the proposed method can reach 97.31%, which is higher than that of the existing machine learning algorithms.	evaluation measures, such confusion matrices, precision, recall, or F1-score. A more thorough examination of these metrics would shed light on how well the model performs in various classes and assist in identifying any possible drawbacks.
45	Distracted Driving Detection with Machine Learning Methods by CNN Based Feature Extraction	AL-DOORI, Shafeeq Kanaan Shakir, Yavuz Selim TASPINAR, and Murat KOKLU	*International Journal of Applied Mathematics Electronics and Computers*	This paper analyses feature extraction-based classification models using convolutional neural networks (CNNs). The SqueezeNet CNN architecture is taught via transfer learning and picture features are extracted beforehand. Images were categorised using machine learning techniques such as k-NN, SVM, and RF, with input from the collected features. The models were trained using a 10-class dataset that included 22,424 driver mistake photos. Classification success rates for k-NN, SVM, and RF models trained on pictures are 98.1%, 95.8%, and 88.7%, respectively. The k-NN model demonstrated the best classification success.	The training and testing phases are the main emphasis of the study; the models' long-term stability and flexibility are not covered. An important area to investigate is how effectively the models function over extended durations, taking into account idea drift or alterations in driving behaviour.
46	Exploring Cognitive Distraction of Galvanic Skin Response while Driving:	Cheng, Chiang-Yu, Wesley Shu, and Han-Ping Tsen	*Journal of Advances in Information Technology Vol* 11.1 (2020).	This research proposal intends to apply the sensor of Galvanic Skin Response (GSR) to measure drivers' non-autonomous cognitive distraction due to the blood glucose variation of diabetes so that it can detect drivers' physiological changes during diabetes outbreak.	Potential differences in GSR responses across diabetes kinds or between diabetics themselves are not addressed in the proposal. The usability of the suggested system depends on

	An Artificial Intelligence Modeling				examining the variability within the diabetes community and comprehending how GSR reacts to various physiological variables. To get a more complete picture of the system's efficacy and possible side effects, it can be helpful to investigate how the suggested system affects drivers' behaviour in the long run and how flexible it is.
47	Distracted driver detection by combining in-vehicle and image data using deep learning	Furkan Omerustaoglu, C. Okan Sakar, Gorkem Kar	*Applied Soft Computing, Volume 96, 2020, 106657, ISSN 1568-4946, https://doi.org/10.1016/j.asoc.2020.106657.*	Author evaluated the system by two different fusion techniques and show that integrating sensor data to image-based driver detection significantly increases the overall performance with both of the fusion techniques. They also showed that the accuracy of the vision-based model increases by fine-tuning the pre-trained CNN model using a related public dataset.	The paper mentions two fusion methods for combining picture and sensor data, but it doesn't compare them. Examining the benefits and drawbacks of various fusion techniques may help direct future studies aimed at streamlining the integration process. Targeted detection algorithms may be developed with guidance from a more thorough examination of the effects of various distracted behaviours on the integrated model's performance.
48	Towards	B. Baheti,	*IEEE*	Author proposed mobileVGG	In this paper, a new

	Computationally Efficient and Realtime Distracted Driver Detection With MobileVGG Network	S. Talbar and S. Gajre	*Transactions on Intelligent Vehicles*, vol. 5, no. 4, pp. 565-574, Dec. 2020, doi: 10.1109/TIV.2020.2995555	architecture with just 2.2M parameters outperforms earlier approaches while achieving 95.24% and 99.75% accuracy on AUC and Statefarm's dataset respectively with less computational complexity and memory requirement.	architecture based on depthwise separable convolutions, named mobileVGG, is proposed. Further investigation into the ways in which these particular convolutional procedures enhance the model's accuracy and efficiency may yield insightful information for future customisation or optimisation.
49	A deep learning-based driver distraction identification framework over edge cloud	Gumaei, Abdu, Mabrook Al-Rakhami, Mohammad Mehedi Hassan, Atif Alamri, Musaed Alhussein, Md Abdur Razzaque, and Giancarlo Fortino	*Neural Comput & Applic* (2020). https://doi.org/10.1007/s00521-020-05328-1	The framework was created with two deep learning models. The first is a customised deep convolutional neural network (CDCNN) model, while the second is a fine-tuned model based on visual geometry group-16 (VGG16). The experimental findings indicated that the first model had an accuracy rate of 99.64% and the second model had an accuracy rate of 99.73% when employing a 10% holdout test set. Furthermore, the first and second models scored 99.36% and 99.57% accuracy rates, respectively, using a 30% holdout test set.	The transparency and reliability of the suggested framework can be improved by addressing the decision-making processes used by these models and offering insights into the characteristics that affect distraction detection.
50	HCF: A Hybrid CNN Framework for Behavior Detection of Distracte	C. Huang, X. Wang, J. Cao, S. Wang and Y. Zhang	*IEEE Access*, vol. 8, pp. 109335-109349, 2020, doi: 10.1109/ACCESS.2020.3001159.	The author proposes a hybrid CNN framework (HCF) that uses deep learning to detect distracted driving behaviours. Experiments show that the HCF achieves a classification accuracy of 96.74%, indicating that it can aid in maintaining safe driving habits.	The study acknowledges that the suggested HCF might not perform well when the camera is positioned differently within the car. Subsequent

	d Drivers.				investigations may concentrate on enhancing the HCF's applicability to various camera configurations within the car.The study points out that the HCF is highly sensitive to light, it could be beneficial to conduct research on methods to improve the model's performance in low light, including incorporating night vision features or using more sensor data.
51	Detection of driver manual distraction via image-based hand and ear recognition	Li, Li, Boxuan Zhong, Clayton Hutmacher Jr, Yulan Liang, William J. Horrey, and Xu Xu	*Accident Analysis & Prevention, Volume 137, 2020, 105432, ISSN 0001-4575, https://doi.org/10.1016/j.aap.2020.105432.*	This publication proposes a unique method to detect driver manual distraction. A total of 106,677 video frames from 20 driving simulator participants were used for training and assessment (50% each). The suggested methodology successfully identified distractions during normal driving, touchscreen use, and phone conversations (F1-scores of 0.84, 0.69, and 0.82, respectively). The total distraction detection F1-score was 0.74. The framework operated at 28 frames per second. The algorithm outperformed previous approaches in terms of accuracy and efficiency.	Subsequent research endeavours might look into methods of reconciling disparate data modalities and alleviating possible partialities, guaranteeing the establishment of a cohesive model that functions admirably in a variety of driving situations.
52	Real-time Detection of	Duy Tran, Ha Manh Do, Jiaxing	*IEEE/RSJ International Conference on Intelligent*	The author developed a relevant and practical application for a voice-alert system that notifies the	A laboratory-based assisted driving testbed was used for the data

	Distracted Driving using Dual Cameras	Lu,Weihua Sheng	*Robots and Systems (IROS)*	distracted motorist to focus on the driving task. We tested the suggested technique on VGG-16, ResNet, and MobileNet-v2 networks. Experimental findings demonstrate that by combining two cameras and VGG-16 networks, we can obtain 96.7% recognition accuracy at a calculation speed of 8 fps.	collecting and validation procedures.The external validity of the study would be improved by examining how well the suggested method generalises to various real-world driving scenarios, including various road conditions, traffic circumstances, and environmental elements.
53	Real Time Detection of driver distraction using CNN	A. Jamsheed V., B. Janet and U. S. Reddy	*International Conference on Smart Systems and Inventive Technology (ICSSIT)*	Author proposed system consist of three models namely, vanilla CNN, vanilla CNN with data augmentation, and CNN with transfer learning. Results obtained from 5 Epochs shows that all the experiments have exceeded 75% accuracy and the best observed result is 97%.	Three distinct models—vanilla CNN, CNN with data augmentation, and CNN with transfer learning—are evaluated in this work. A thorough comparison might provide light on the relative advantages and disadvantages of various approaches.Further research could investigate techniques to improve the interpretability of the model decisions.
54	Aggregating CNN and HOG features for Real-Time Distracted Driver	M. R. Arefin, F. Makhmudkhujaev, O. Chae and J. Kim	*IEEE International Conference on Consumer Electronics (ICCE)*	The author developed a robust strategy that comprises of modifying the AlexNet architecture and aggregating HOG characteristics. In comparison to AlexNet, the number of parameters in our model is reduced from 62.3M to 9.7M, and assessment on a publically accessible dataset	Research methods to provide meaningful explanations for the model's predictions, which can be crucial for gaining trust from end-users and regulatory

	Detection			indicates that our model has a comparative accuracy of 93.19% versus 93.65% for the original AlexNet.	bodies could be implemented.
55	Real-time detection of distracted driving based on deep learning	Duy Tran, Ha Manh Do, Weihua Sheng, He Bai, and Girish Chowdhary	*IET Intelligent transport system https://doi.org/10.1049/iet-its.2018.5172*	Author developed a conversational warning system that alerts the driver in real-time when he/she does not focus on the driving task. Experimental results show that the proposed approach outperforms the baseline one which has only 256 neurons in the fully-connected layers	Future research could examine the advantages and synergies of merging other modalities, such as body postures and facial expressions, in order to develop a distracted driving detection system that is more thorough and precise. An analysis contrasting completely linked layers with conventional classifiers could bring insight into the advantages of each strategy.
56	Drive-Net: Convolutional Network for Driver Distraction Detection	M. S. Majdi, S. Ram, J. T. Gill and J. J. Rodríguez	*IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI)*, Las Vegas, NV, USA, 2018, pp. 1-4, doi: 10.1109/SSIAI.2018.8470309.	Drive-Net employs a convolutional neural network (CNN) and a random decision forest to identify driver photos.The author evaluated the approaches using a publicly accessible database of photographs obtained in a controlled setting, which included around 22425 photos manually annotated by an expert. The results demonstrate that Drive-Net has a detection accuracy of 95%, which is 2% higher than the best results produced on the same database using other approaches.	Assessing the possible biases incorporated in the model's training data, as well as their ramifications in real-world applications, is a significant field of study gap. Investigating the ethical implications of Drive-Net implementation in various groups, as well as mitigating any biases, should be top priorities.
57	An Adaptive	S. M. Iranmanesh	*IEEE Transactions*	This method considers the driver distraction in parallel to	The assessment findings show a

	Forward Collision Warning Framework Design Based on Driver Distraction	, H. Nourkhiz Mahjoub, H. Kazemi and Y. P. Fallah	*on Intelligent Transportation Systems, vol. 19, no. 12, pp. 3925-3934, Dec. 2018, doi: 10.1109/TITS.2018.2791437*	fine-tune the calculated threshold in accordance with driver cognitive state.The framework performance is evaluated over two realistic driving datasets. An approximately 80% false warning reduction is observed in analyzed safe scenarios	considerable reduction in false alarms in the analysed safe scenarios. However, there remains a gap in comprehending the framework's long-term viability and stability. Long-term studies that monitor the method's performance over time can shed light on its dependability and any difficulties that may occur over time.
58	Driver Drowsiness Detection Using Condition-Adaptive Representation Learning Framework	J. Yu, S. Park, S. Lee and M. Jeon	*IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 11, pp. 4206-4218, Nov. 2019, doi: 10.1109/TITS.2018.2883823	The proposed framework includes four models: spatiotemporal representation learning, scene condition comprehension, feature fusion, and sleepiness detection. The suggested methodology is assessed using the NTHU sleepy driver detection video dataset. The experimental findings suggest that the framework outperforms current sleepiness detection approaches based on visual analysis.	The proposed approach uses visual analysis to identify tiredness. Integrating other modalities, such as physiological inputs or acoustic cues, may improve the system's overall accuracy and dependability. Cross-modal integration has the potential to improve sleepy driver detection.
59	Real-time Distracted Driver Posture Classification	Yehya Abouelnaga, Hesham M. Eraqi, Mohamed N. Moustafa	*arXiv preprint arXiv:1706.09498* (2017).	The author suggested a new approach that achieves 95.98% driving posture estimate categorization accuracy. The system is made up of a genetically weighted ensemble of Convolutional Neural Networks (CNNs).The authors demonstrated a thinner version of their ensemble that achieved a classification accuracy of	Future research could be conducted to create a face and hands detector that is more effective in minimising computing costs without sacrificing accuracy. A thorough analysis that includes measurements like

				94.29% while operating in real time.	accuracy, precision, recall, and F1 score can shed light on how well temporal features differentiate between various driving stances.
60	Visual-Manual Distraction Detection Using Driving Performance Indicators With Naturalistic Driving Data	Z. Li, S. Bao, I. V. Kolmanovsky and X. Yin	*IEEE Transactions on Intelligent Transportation Systems*	The author created a nonlinear autoregressive exogenous (NARX) driving model that predicts vehicle speed using range (distance headway), range rate, and speed history.A support vector machine is trained to identify driving attention using two parameters from the NARX model: steering entropy and mean absolute speed prediction error. .	The NARX model's mean absolute speed prediction error and steering entropy are chosen by the authors as features for distracted detection. A more thorough examination of feature selection and sensitivity to identify the most useful features may be part of future work.

Research Gap and scope of future work:

Road safety remains a critical concern, and the emergence of machine learning has opened up new options for solving the challenges posed by risky driving behaviours. This extensive review looks at the landscape of machine learning approaches used to detect reckless driving. While investigating existing approaches, models, and data sources, a clear research need arises. Despite significant advances, there is a need for more standardised assessment measures and datasets to enable meaningful comparisons across various methodologies.
The current research gap centres on the lack of a unified framework for evaluating the effectiveness of machine learning models in reckless driving detection. Diverse datasets, varying feature extraction techniques, and distinct evaluation criteria hinder a comprehensive understanding of the strengths and limitations of different approaches. Standardization in these aspects would not only enhance the reproducibility of results but also foster a more systematic advancement of the field.
Future research endeavors should focus on establishing standardized evaluation protocols, including benchmark datasets and performance metrics. Researchers can compare their suggested efforts with those of others on a near-standard dataset if additional relevant datasets with specified qualities become publically accessible. Previous studies have shown that integrating machine learning techniques with geographical and temporal information improves the understanding of the actions of the driver. As a result, driver distractions can be precisely identified.To provide deep architectures more data, data augmentation is required. With additional processing power, the accuracy may be increased by building networks from scratch,

like capsnet3D, using the Kinetics dataset and fine-tuning them using data on driver manual distraction.

Eye tracking-based driver distraction detection algorithms aim to identify visual distraction. All algorithms can be fitted into a common framework: determine whether or not the driver is looking at the road, convert this information into a continuous estimate of (visual) distraction, and then use some rule, often a threshold, to determine whether the estimated level of distraction should be considered distracted or attentive. The fundamental shortcoming of these techniques is that they do not account for the present traffic scenario. This might be accomplished by enabling the driving-relevant field to alter dynamically over time. Future study is required to (a) establish the ideal driving field for various traffic conditions and traffic environments, and (b) create technologies to measure the present traffic situation and traffic environment.

Future studies are required to (a) examine the physiology of eye movements while driving, (b) create more accurate remote eye tracking technology so that these quick and small eye movements can be measured, and (c) create algorithms that reliably and accurately identify various eye movements such as fixations, saccades, and smooth pursuit from the continuous data stream.

Acknowledgement: The paper merely represents the author's point of view, and the Commission accepts no responsibility for how the information included in it is used.

References:

1 Qibtiah, Raja Mariatul, Zalhan Mohd Zin, and Mohd Fadzil Abu Hassan. "Artificial intelligence system for driver distraction by stacked deep learning classification." *Bulletin of Electrical Engineering and Informatics* 12.1 (2023): 365-372.

2 Aljohani, Abeer A. "Real-time driver distraction recognition: A hybrid genetic deep network based approach." *Alexandria Engineering Journal* 66 (2023): 377-389.

3 Wang, Jing, and ZhongCheng Wu. "Driver distraction detection via multi-scale domain adaptation network." *IET Intelligent Transport Systems* (2023).

4 Aboah, Armstrong, et al. "Deepsegmenter: Temporal action localization for detecting anomalies in untrimmed naturalistic driving videos." *arXiv preprint arXiv:2304.08261* (2023).

5 Ping, Peng, et al. "Distracted driving detection based on the fusion of deep learning and causal reasoning." *Information Fusion* 89 (2023): 121-142.

6 Jayantha, Gummula, And P. Velayutham. "Driver Drowsiness Monitoring System Using Visual behaviour and Machine Learning." *Journal of Engineering Sciences* 14.01 (2023).

7 Jahan, Israt, et al. "4D: a real-time driver drowsiness detector using deep learning." *Electronics* 12.1 (2023): 235.

8 Rahman, Mohammed Shaiqur, et al. "Synthetic distracted driving (syndd1) dataset for analyzing distracted behaviors and various gaze zones of a driver." *Data in brief* 46 (2023): 108793.

9 Parvez M, Muzammil, et al. "Advanced Driver Fatigue Detection by Integration of OpenCV DNN Module and Deep Learning." *Engineering Proceedings* 34.1 (2023): 15.

10 Bajaj, Jaspreet Singh, et al. "System and method for driver drowsiness detection using behavioral and sensor-based physiological measures." *Sensors* 23.3 (2023): 1292.

11 Rahman, M. Ashifur, Subasish Das, and Xiaoduan Sun. "Understanding the drowsy driving crash patterns from correspondence regression analysis." *Journal of safety research* 84 (2023): 167-181.

12 Akrout, Belhassen, and Sana Fakhfakh. "How to Prevent Drivers before Their Sleepiness Using Deep Learning-Based Approach." *Electronics* 12.4 (2023): 965.

13 Bahmani, Zahra. "Network Analysis of Facial Behaviours for Non-Contact Driver Distraction Detection."

14 Oppelt, Maximilian P., et al. "ADABase: A Multimodal Dataset for Cognitive Load Estimation." *Sensors* 23.1 (2023): 340.

15 Xue, Qingwan, et al. "Young Novice Drivers' Cognitive Distraction Detection: Comparing Support Vector Machines and Random Forest Model of Vehicle Control Behavior." *Sensors* 23.3 (2023): 1345.

16 Yan, X., Zou, Z., Feng, S. *et al.* Learning naturalistic driving environment with statistical realism. *Nat Commun* **14**, 2037 (2023). https://doi.org/10.1038/s41467-023-37677-5

17 A. Misra, S. Samuel, S. Cao and K. Shariatmadari, "Detection of Driver Cognitive Distraction Using Machine Learning Methods," in IEEE Access, vol. 11, pp. 18000-18012, 2023, doi: 10.1109/ACCESS.2023.3245122.

18. Wei Song, Guangde Zhang, Yicheng Long,"Identification of dangerous driving state based on lightweight deep learning model",Computers and Electrical Engineering,Volume 105,2023,108509,ISSN 0045-7906,https://doi.org/10.1016/j.compeleceng.2022.108509

19 Eduardo Candela, Olivier Doustaly, Leandro Parada, Felix Feng, Yiannis Demiris, Panagiotis Angeloudis,"Risk-aware controller for autonomous vehicles using model-based collision prediction and reinforcement learning"Artificial Intelligence,Volume 320,2023,103923,ISSN 0004-3702,https://doi.org/10.1016/j.artint.2023.103923

20 Sahoo, G.K., Das, S.K. & Singh, P. A deep learning-based distracted driving detection solution implemented on embedded system. Multimed Tools Appl 82, 11697–11720 (2023). https://doi.org/10.1007/s11042-022-13450-6

21 Yu, Wangpengfei, Yubin Qian, Jiejie Xu, Hongtao Sun, and Junxiang Wang. 2023. "Driving Decisions for Autonomous Vehicles in Intersection Environments: Deep Reinforcement Learning Approaches with Risk Assessment" *World Electric Vehicle Journal* 14, no. 4: 79. https://doi.org/10.3390/wevj14040079

22 Yan, Xintong, Jie He, Guanhe Wu, Changjian Zhang, and Chenwei Wang. 2022. "A Proactive Recognition System for Detecting Commercial Vehicle Driver's Distracted Behavior" *Sensors* 22, no. 6: 2373. https://doi.org/10.3390/s22062373

23 M. Guria and B. Bhowmik, "IoT-Enabled Driver Drowsiness Detection Using Machine Learning," 2022 Seventh International Conference on Parallel, Distributed and Grid Computing (PDGC), Solan, Himachal Pradesh, India, 2022, pp. 519-524, doi: 10.1109/PDGC56933.2022.10053235.

24 Ma, Xiaolong, Qiang Yu, and Jian bei Liu. 2022. "Modeling Urban Freeway Rear-End Collision Risk Using Machine Learning Algorithms" *Sustainability* 14, no. 19: 12047. https://doi.org/10.3390/su141912047

25 Malik, Meenakshi, Rainu Nandal, Surjeet Dalal, Vivek Jalglan, and Dac-Nhuong Le. "Deriving Driver Behavioral Pattern Analysis and Performance Using Neural Network Approaches." *Intelligent Automation & Soft Computing* 32, no. 1 (2022).

26 Eunji Kim and others, Safety monitoring system of personal mobility driving using deep learning, Journal of Computational Design and Engineering, Volume 9, Issue 4, August 2022, Pages 1397–1409, https://doi.org/10.1093/jcde/qwac061

27 Jiaxun Cui, Hang Qiu, Dian Chen, Peter Stone, Yuke Zhu; Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 17252-17262

28 Alkinani, Monagi H., Wazir Zada Khan, Quratulain Arshad, and Mudassar Raza. 2022. "HSDDD: A Hybrid Scheme for the Detection of Distracted Driving through Fusion of Deep Learning and Handcrafted Features" *Sensors* 22, no. 5: 1864. https://doi.org/10.3390/s22051864

29 B. Qin, J. Qian, Y. Xin, B. Liu and Y. Dong, "Distracted Driver Detection Based on a CNN With Decreasing Filter Size," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 7, pp. 6922-6933, July 2022, doi: 10.1109/TITS.2021.3063521

30 N. K. Vaegae, K. K. Pulluri, K. Bagadi and O. O. Oyerinde, "Design of an Efficient Distracted Driver Detection System: Deep Learning Approaches," in *IEEE Access*, vol. 10, pp. 116087-116097, 2022, doi: 10.1109/ACCESS.2022.3218711

31 Aljasim, Mustafa, and Rasha Kashef. 2022. "E2DR: A Deep Learning Ensemble-Based Driver Distraction Detection with Recommendations Model" *Sensors* 22, no. 5: 1858. https://doi.org/10.3390/s22051858

32 P. -W. Lin and C. -M. Hsu, "Innovative Framework for Distracted-Driving Alert System Based on Deep Learning," in *IEEE Access*, vol. 10, pp. 77523-77536, 2022, doi: 10.1109/ACCESS.2022.3186674

33 Hozhabr Pour, Hawzhin, Frédéric Li, Lukas Wegmeth, Christian Trense, Rafał Doniec, Marcin Grzegorzek, and Roland Wismüller. 2022. "A Machine Learning Framework for Automated Accident Detection Based on Multimodal Sensors in Cars" *Sensors* 22, no. 10: 3634. https://doi.org/10.3390/s22103634

34 Wang, Jing, Zhong Cheng Wu, Fang Li, and Jun Zhang. 2021. "A Data Augmentation Approach to Distracted Driving Detection" *Future Internet* 13, no. 1: 1. https://doi.org/10.3390/fi13010001

35 Zafar Iqbal, Majid I. Khan, Shahid Hussain, Asad Habib, and Átila Bueno. 2021. An Efficient Traffic Incident Detection and Classification Framework by Leveraging the Efficacy of Model Stacking. Complex. 2021 (2021). https://doi.org/10.1155/2021/5543698

36 A. Ezzouhri, Z. Charouh, M. Ghogho and Z. Guennoun, "Robust Deep Learning-Based Driver Distraction Detection and Classification," in *IEEE Access*, vol. 9, pp. 168080-168092, 2021, doi: 10.1109/ACCESS.2021.3133797

37 A. Kashevnik, R. Shchedrin, C. Kaiser and A. Stocker, "Driver Distraction Detection Methods: A Literature Review and Framework," in *IEEE Access*, vol. 9, pp. 60063-60076, 2021, doi: 10.1109/ACCESS.2021.3073599.

38 H. Varun Chand , J. Karthikeyan 2021 CNN Based Driver Drowsiness Detection System Using Emotion Analysis 2021 DOI:10.32604/iasc.2022.020008

39 Peppes, Nikolaos, Theodoros Alexakis, Evgenia Adamopoulou, and Konstantinos Demestichas. 2021. "Driving Behaviour Analysis Using Machine and Deep Learning Methods for Continuous Streams of Vehicular Data" *Sensors* 21, no. 14: 4704. https://doi.org/10.3390/s21144704

40 Kalra, Nidhi, Raman Kumar Goyal, Anshu Parashar, Jaskirat Singh, and Gagan Singla. "Driving Style Recognition System Using Smartphone Sensors Based on Fuzzy Logic." *Computers, Materials & Continua* 69, no. 2 (2021).

41 J. R. Macalisang, A. S. Alon, M. F. Jardiniano, D. C. P. Evangelista, J. C. Castro and M. L. Tria, "Drive-Awake: A YOLOv3 Machine Vision Inference Approach of Eyes Closure for Drowsy Driving Detection," 2021 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET), Kota Kinabalu, Malaysia, 2021, pp. 1-5, doi:10.1109/IICAIET51634.2021.9573811.

42 Koay, Hong Vin, Joon Huang Chuah, Chee-Onn Chow, Yang-Lang Chang, and Bhuvendhraa Rudrusamy. 2021. "Optimally-Weighted Image-Pose Approach (OWIPA) for Distracted Driver Detection and Classification" *Sensors* 21, no. 14: 4837. https://doi.org/10.3390/s21144837

43 Jain, D.K., Jain, R., Lan, X. et al. Driver distraction detection using capsule network. Neural Comput & Applic 33, 6183–6196 (2021). https://doi.org/10.1007/s00521-020-05390-9

44 Rao, X., Lin, F., Chen, Z. et al. Distracted driving recognition method based on deep convolutional neural network. J Ambient Intell Human Comput 12, 193–200 (2021). https://doi.org/10.1007/s12652-019-01597-4

45 Aldoori, Shafeeq & Taspinar, Yavuz & Koklu, Murat. (2021). Distracted Driving Detection with Machine Learning Methods by CNN Based Feature Extraction. International Journal of Applied Mathematics Electronics and Computers. 9. 116-121. 10.18100/ijamec.1035749.

46 Cheng, Chiang-Yu & Shu, Wesley Szuway & Han-Ping, Tsen. (2020). Exploring Cognitive Distraction of Galvanic Skin Response while Driving: An Artificial Intelligence Modeling. Journal of Advances in Information Technology. 35-39. 10.12720/jait.11.1.35-39.

47 Furkan Omerustaoglu, C. Okan Sakar, and Gorkem Kar. 2020. Distracted driver detection by combining in-vehicle and image data using deep learning. Appl. Soft Comput. 96, C (Nov 2020). https://doi.org/10.1016/j.asoc.2020.106657

48 B. Baheti, S. Talbar and S. Gajre, "Towards Computationally Efficient and Realtime Distracted Driver Detection With MobileVGG Network," in *IEEE Transactions on Intelligent Vehicles*, vol. 5, no. 4, pp. 565-574, Dec. 2020, doi: 10.1109/TIV.2020.2995555.

49 Gumaei, A., Al-Rakhami, M., Hassan, M.M. et al. A deep learning-based driver distraction identification framework over edge cloud. Neural Comput & Applic (2020). https://doi.org/10.1007/s00521-020-05328-1

50 C. Huang, X. Wang, J. Cao, S. Wang and Y. Zhang, "HCF: A Hybrid CNN Framework for Behavior Detection of Distracted Drivers," in *IEEE Access*, vol. 8, pp. 109335-109349, 2020, doi: 10.1109/ACCESS.2020.3001159.

51 Li, Li & Zhong, Boxuan & Hutmacher, Clayton & Liang, Yulan & Horrey, William & Xu, Xu. (2020). Detection of driver manual distraction via image-based hand and ear recognition. Accident; analysis and prevention. 137. 105432. 10.1016/j.aap.2020.105432.

52. D. Tran, H. M. Do, J. Lu and W. Sheng, "Real-time Detection of Distracted Driving using Dual Cameras," *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Las Vegas, NV, USA, 2020, pp. 2014-2019, doi: 10.1109/IROS45743.2020.9340921.

53 A. Jamsheed V., B. Janet and U. S. Reddy, "Real Time Detection of driver distraction using CNN," *2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT)*, Tirunelveli, India, 2020, pp. 185-191, doi: 10.1109/ICSSIT48917.2020.9214233.

54 M. R. Arefin, F. Makhmudkhujaev, O. Chae and J. Kim, "Aggregating CNN and HOG features for Real-Time Distracted Driver Detection," *2019 IEEE International Conference on Consumer Electronics (ICCE)*, Las Vegas, NV, USA, 2019, pp. 1-3, doi: 10.1109/ICCE.2019.8661970.

55 D. Tran, H. M. Do, J. Lu and W. Sheng, "Real-time Detection of Distracted Driving using Dual Cameras," *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Las Vegas, NV, USA, 2020, pp. 2014-2019, doi: 10.1109/IROS45743.2020.9340921

56 M. S. Majdi, S. Ram, J. T. Gill and J. J. Rodríguez, "Drive-Net: Convolutional Network for Driver Distraction Detection," *2018 IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI)*, Las Vegas, NV, USA, 2018, pp. 1-4, doi: 10.1109/SSIAI.2018.8470309.

57 S. M. Iranmanesh, H. Nourkhiz Mahjoub, H. Kazemi and Y. P. Fallah, "An Adaptive Forward Collision Warning Framework Design Based on Driver Distraction," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 12, pp. 3925-3934, Dec. 2018, doi: 10.1109/TITS.2018.2791437.

58 J. Yu, S. Park, S. Lee and M. Jeon, "Driver Drowsiness Detection Using Condition-Adaptive Representation Learning Framework," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 11, pp. 4206-4218, Nov. 2019, doi: 10.1109/TITS.2018.2883823

59 Abouelnaga, Yehya, Hesham M. Eraqi, and Mohamed N. Moustafa. "Real-time distracted driver posture classification." *arXiv preprint arXiv:1706.09498* (2017).

60 Z. Li, S. Bao, I. V. Kolmanovsky and X. Yin, "Visual-Manual Distraction Detection Using Driving Performance Indicators With Naturalistic Driving Data," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 8, pp. 2528-2535, Aug. 2018, doi: 10.1109/TITS.2017.2754467