

MINISTRY OF SCIENCE AND HIGHER EDUCATION OF THE REPUBLIC OF KAZAKHSTAN
ҚАЗАҚСТАН РЕСПУБЛИКАСЫНЫҢ ҒЫЛЫМ ЖӘНЕ ЖОҒАРЫ БІЛІМ МИНИСТРЛІГІ
МИНИСТЕРСТВО НАУКИ И ВЫСШЕГО ОБРАЗОВАНИЯ РЕСПУБЛИКИ КАЗАХСТАН
KAZAKHSTAN



**INTERNATIONAL JOURNAL OF INFORMATION AND COMMUNICATION
TECHNOLOGIES**

Published since 2020.
Volume 7. 1 (25). 2026
January–March

**ХАЛЫҚАРАЛЫҚ АҚПАРАТТЫҚ ЖӘНЕ КОММУНИКАЦИЯЛЫҚ
ТЕХНОЛОГИЯЛАР ЖУРНАЛЫ**

2020 жылдан бері шығарылады
Том 7. 1 (25). 2026
Қаңтар-Наурыз

**МЕЖДУНАРОДНЫЙ ЖУРНАЛ ИНФОРМАЦИОННЫХ И
КОММУНИКАЦИОННЫХ ТЕХНОЛОГИЙ**

Издается с 2020 г.
Том 7. 1 (25). 2026
Январь-Март

Свидетельство о постановке на учет периодического печатного издания в Министерство информации и общественного развития Республики Казахстан № KZ82VPY00020475, выданное от 20.02.2020 г.

Зарегистрировано в Международном центре регистрации серийных изданий ISSN (ЮНЕСКО, Париж, Франция). ISSN 2708–2032 (print), ISSN 2708–2040 (online)

Журнал входит в Перечень научных изданий, рекомендуемых КОКНВО МНВО РК для публикации основных результатов научной деятельности.

EDITOR-IN-CHIEF:

Kateryna Kolesnikova — Doctor of Technical Sciences, professor, Vice-Rector for Research, International Information Technology University (Kazakhstan)

DEPUTY EDITOR-IN-CHIEF:

Madina Ipalakova — Candidate of Technical Sciences, associate professor, Director of the Research Department, International Information Technology University (Kazakhstan)

EDITORIAL BOARD:

Abdul Razak — PhD, professor, Department of Cybersecurity, International Information Technology University (Kazakhstan)

Lucio Tommaso De Paolis — Director of the R&D Department of the AVR Laboratory, Department of Engineering for Innovation, University of Salento (Italy)

Liz Bacon — Professor, Deputy Vice-Chancellor, Abertay University (United Kingdom)

Michele Pagano — PhD, Professor, University of Pisa (Italy)

Mukhtarbay Otelbayev — Doctor of Physical and Mathematical Sciences, professor, academician of the National Academy of Sciences of the Republic of Kazakhstan, professor of the Department of Mathematical and Computer Modeling, International Information Technology University (Kazakhstan)

Bolatbek Rysbauly — Doctor of Physical and Mathematical Sciences, professor, professor of the Department of Computing and Data Science, Astana IT University (Kazakhstan)

Yevgeniya Daineko — PhD, research professor, Department of Information Systems, International Information Technology University (Kazakhstan)

Nurzhan Duzbayev — PhD, associate professor, Vice-Rector for Digitalization and Innovation, International Information Technology University (Kazakhstan)

Bakhtgerai Sinchev — Doctor of Technical Sciences, professor, Department of Information Systems, International Information Technology University (Kazakhstan)

Nurgul Seilova — Candidate of Technical Sciences, Dean of the Faculty of Computer Technologies and Cybersecurity, International Information Technology University (Kazakhstan)

Ardak Mukhamediyeva — Candidate of Economic Sciences, Dean of the Faculty of Business, Media and Management, International Information Technology University (Kazakhstan)

Zamira Abdikalikova — PhD, associate professor, Head of the Department of Mathematical and Computer Modeling, International Information Technology University (Kazakhstan)

Yerlan Shildibekov — PhD, associate professor, Head of the Department of Economics and Business, International Information Technology University (Kazakhstan)

Damilya Yeskendiroya — Candidate of Technical Sciences, associate professor, Head of the Department of Cybersecurity, International Information Technology University (Kazakhstan)

Aigul Niyazgulova — Candidate of Philological Sciences, Professor, Head of the Department of Media Communications and History of Kazakhstan, International Information Technology University (Kazakhstan)

Altai Aitmagambetov — Candidate of Technical Sciences, Professor, Department of Radio Engineering, Electronics and Telecommunications, International Information Technology University (Kazakhstan)

Yelena Bakhtiyarova — Candidate of Technical Sciences, associate professor, Head of the Department of Radio Engineering, Electronics and Telecommunications, International Information Technology University (Kazakhstan)

Kanibek Sansyzbay — PhD, research professor, Department of Cybersecurity, International Information Technology University (Kazakhstan)

Sakhybay Tynymbayev — Candidate of Technical Sciences, Professor, Research Professor, Department of Computer Engineering, International Information Technology University (Kazakhstan)

Ali Abd Almisreb — PhD, associate professor, Department of Cybersecurity, International Information Technology University (Kazakhstan)

Mohamed Ahmed Hamada — PhD, associate professor, Department of Information Systems, International Information Technology University (Kazakhstan)

Yang Im Chu — PhD, Professor, Gachon University (South Korea)

Tadeusz Wallas — PhD, Vice-Rector, Adam Mickiewicz University (Poland)

Orken Mamyrbayev — PhD, Deputy Director for Science, RSE Institute of Information and Computational Technologies, Committee for Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Kazakhstan)

Sergey Bushuyev — Doctor of Technical Sciences, professor, Director of the Ukrainian Project Management Association "UKRNET," Head of the Department of Project Management, Kyiv National University of Construction and Architecture (Ukraine)

Svetlana Beloshitskaya — Doctor of Technical Sciences, professor, Department of Computing and Data Science, Astana IT University (Kazakhstan)

MANAGING EDITOR

Raushan Mrzabayeva — Master of Science, editor, International Information Technology University (Kazakhstan)

International Journal of Information and Communication Technologies

Periodicity: 4 times a year.

Languages: Kazakh, Russian, English

DOI prefix: 10.54309

ISSN 2708-2032 (print)

ISSN 2708-2040 (online)

Thematic focus: "Information technology"; "Digital technologies in the development of socio-economic systems"; "Information security and communication technologies".

Distribution: Materials are distributed under the Creative Commons Attribution 4.0

Journal website: <https://journal.iitu.edu.kz>

Owner: International Information Technology University JSC (Almaty).

Copyright: © International Journal of Information and Communication Technologies, 2026

РЕДАКЦИЯ

БАС РЕДАКТОР:

Колесникова Катерина Викторовна — техника ғылымдарының докторы, профессор, Халықаралық ақпараттық технологиялар университетінің ғылыми-зерттеу қызметі жөніндегі проректор (Қазақстан)

БАС РЕДАКТОРДЫҢ ОРЫНБАСАРЫ:

Ипалакова Мадина Түлегеновна — техника ғылымдарының кандидаты, қауымдастырылған профессор, Халықаралық ақпараттық технологиялар университетінің ғылыми-зерттеу қызметі жөніндегі департамент директоры (Қазақстан)

РЕДАКЦИЯЛЫҚ АЛҚА:

Разак Абдул — PhD, Халықаралық ақпараттық технологиялар университеті киберқауіпсіздік кафедрасының профессоры (Қазақстан)

Лучио Томмазо де Паолис — Саленто Университеті (Италия) инновация және технологиялық инжиниринг департаменті AVR зертханасының зерттеу және әзірлеу бөлімінің директоры

Лиз Бэкон — профессор, Абертей Университеті (Ұлыбритания) вице-канцлерінің орынбасары

Микеле Пагано — PhD, Пиза Университетінің (Италия) профессоры

Өтелбаев Мұхтарбай Өтелбайұлы — физика-математика ғылымдарының докторы, профессор, ҚР ҰҒА академигі, Халықаралық ақпараттық технологиялар университеті математика және компьютерлік модельдеу кафедрасының профессоры (Қазақстан)

Рысбайұлы Болатбек — физика-математика ғылымдарының докторы, профессор, Есептеу және деректер ғылымдары департаментінің профессоры, Astana IT University (Қазақстан)

Дайнеко Евгения Александровна — PhD, Халықаралық ақпараттық технологиялар университеті ақпараттық жүйелер кафедрасының профессор-зерттеушісі (Қазақстан)

Дузаев Нуржан Тоқсуажасвич — PhD, қауымдастырылған профессор, Халықаралық ақпараттық технологиялар университеті цифрландыру және инновациялар жөніндегі проректор (Қазақстан)

Синчев Бахтгерей Кусанович — техника ғылымдарының докторы, профессор, Халықаралық ақпараттық технологиялар университеті ақпараттық жүйелер кафедрасының профессоры (Қазақстан)

Сейлова Нургуль Абадуллаевна — техника ғылымдарының докторы, Халықаралық ақпараттық технологиялар университеті компьютерлік технологиялар және киберқауіпсіздік факультетінің деканы (Қазақстан)

Мухамедиева Ардак Габитовна — экономика ғылымдарының кандидаты, Халықаралық ақпараттық технологиялар университеті бизнес медиа және басқару факультетінің деканы (Қазақстан)

Абикаликова Замира Тұрсынбаевна — PhD, қауымдастырылған профессор, Халықаралық ақпараттық технологиялар университеті математика және компьютерлік модельдеу кафедрасының меңгерушісі (Қазақстан)

Шильдибеков Ерлан Жаржанович — PhD, қауымдастырылған профессор, Халықаралық ақпараттық технологиялар университеті экономика және бизнес кафедрасының меңгерушісі (Қазақстан)

Дамеля Максұтовна Ескендірова — техника ғылымдарының кандидаты, қауымдастырылған профессор, Халықаралық ақпараттық технологиялар университеті киберқауіпсіздік кафедрасының меңгерушісі (Қазақстан)

Ниязгулова Айгуль Аскарбековна — филология ғылымдарының кандидаты, доцент, профессор, Халықаралық ақпараттық технологиялар университеті медиакоммуникация және Қазақстан тарихы кафедрасының меңгерушісі (Қазақстан)

Айтмағамбетов Алтай Зуфарович — техника ғылымдарының кандидаты, Халықаралық ақпараттық технологиялар университеті радиотехника, электроника және телекоммуникация кафедрасының профессоры (Қазақстан)

Бахтиярова Елена Ажибековна — техника ғылымдарының кандидаты, қауымдастырылған профессор, Халықаралық ақпараттық технологиялар университеті радиотехника, электроника және телекоммуникация кафедрасының меңгерушісі (Қазақстан)

Канибек Сансызбай — PhD, қауымдастырылған профессор, Халықаралық ақпараттық технологиялар университеті киберқауіпсіздік кафедрасының профессор-зерттеушісі (Қазақстан)

Тынымбаев Сахибай — техника ғылымдарының кандидаты, профессор, Халықаралық ақпараттық технологиялар университеті компьютерлік инженерия кафедрасының профессор-зерттеушісі (Қазақстан)

Алмисреб Али Абд — PhD, Халықаралық ақпараттық технологиялар университеті киберқауіпсіздік кафедрасының қауымдастырылған профессоры (Қазақстан)

Мохамед Ахмед Хамада — PhD, Халықаралық ақпараттық технологиялар университеті ақпараттық жүйелер кафедрасының қауымдастырылған профессоры (Қазақстан)

Янг Им Чу — PhD, Гачон университетінің профессоры (Оңтүстік Корея)

Тадеш Валлас — PhD, Адам Мицкевич атындағы (Польша) университеттің проректоры

Мамырбаев Оркен Жумажанович — PhD, ҚР ҒЖБМ Ғылым комитеті ақпараттық және есептеу технологиялары институты ӨМК директорының ғылым жөніндегі орынбасары (Қазақстан)

Бушув Сергей Дмитриевич — техника ғылымдарының докторы, профессор, Украинаның "УКРНЕТ" жобаларды басқару қауымдастығының директоры, Киев ұлттық құрылыс және сулест университеті жобаларды басқару кафедрасының меңгерушісі (Украина)

Белюшицкая Светлана Васильевна — техника ғылымдарының докторы, доцент, Astana IT University есептеу және деректер ғылымы кафедрасының профессоры (Қазақстан)

ЖАУАПТЫ РЕДАКТОР:

Мрзабаева Раушан Жалиевна — магистр, Халықаралық ақпараттық технологиялар университетінің редакторы (Қазақстан)

Халықаралық ақпараттық және коммуникациялық технологиялар журналы

ISSN 2708–2032 (print)

ISSN 2708–2040 (online)

Префикс DOI: 10.54309

Мерзімділігі: жылына 4 рет.

Басылым тілі: қазақ, орыс, ағылшын.

Тақырып бағыты: "Ақпараттық технологиялар"; "Ақпараттық қауіпсіздік және коммуникациялық технологиялар"; "Әлеуметтік-экономикалық жүйелерді дамытудағы цифрлық технология".

Журнал сайты: <https://journal.iitu.edu.kz>

Тарату: материалдар Creative Commons Attribution 4.0 лицензиясы бойынша таратылады

Меншік иесі: АҚ «Халықаралық ақпараттық технологиялар университеті» (Алматы қ.).

Авторлық құқық: © Халықаралық ақпараттық және коммуникациялық технологиялар журналы, 2026

РЕДАКЦИЯ

ГЛАВНЫЙ РЕДАКТОР:

Колесникова Катерина Викторовна — доктор технических наук, профессор, проректор по научно-исследовательской деятельности Международного университета информационных технологий (Казахстан)

ЗАМЕСТИТЕЛЬ ГЛАВНОГО РЕДАКТОРА:

Ипалакова Мадина Тулегеновна — кандидат технических наук, ассоциированный профессор, директор департамента по научно-исследовательской деятельности Международного университета информационных технологий (Казахстан)

РЕДАКЦИОННАЯ КОЛЛЕГИЯ:

Разак Абдул — PhD, профессор кафедры кибербезопасности Международного университета информационных технологий (Казахстан)

Лучио Томмазо де Паолис — директор отдела исследований и разработок лаборатории AVR департамента инноваций и технологического инжиниринга Университета Саленто (Италия)

Лиз Бэкон — профессор, заместитель вице-канцлера Университета Абертей (Великобритания)

Микеле Пагано — PhD, профессор Университета Пизы (Италия)

Отелбаев Мухтарбай Отелбайулы — доктор физико-математических наук, профессор, академик НАН РК, профессор кафедры математического и компьютерного моделирования Международного университета информационных технологий (Казахстан)

Рысбайулы Болатбек — доктор физико-математических наук, профессор, профессор Astana IT University (Казахстан)

Дайнеко Евгения Александровна — PhD, профессор-исследователь кафедры информационных систем Международного университета информационных технологий (Казахстан)

Дузбаев Нуржан Токкужаевич — PhD, ассоциированный профессор, проректор по цифровизации и инновациям Международного университета информационных технологий (Казахстан)

Синчев Бахтгерей Куспанович — доктор технических наук, профессор, профессор кафедры информационных систем Международного университета информационных технологий (Казахстан)

Сейлова Нургуль Абадуллаевна — кандидат технических наук, декан факультета компьютерных технологий и кибербезопасности Международного университета информационных технологий (Казахстан)

Мухамедиева Ардак Габитовна — кандидат экономических наук, декан факультета бизнеса медиа и управления Международного университета информационных технологий (Казахстан)

Абдикаликова Замира Турсынбаевна — PhD, ассоциированный профессор, заведующая кафедрой математического и компьютерного моделирования Международного университета информационных технологий (Казахстан)

Шильдибеков Ерлан Жаржанович — PhD, ассоциированный профессор, заведующий кафедрой экономики и бизнеса Международного университета информационных технологий (Казахстан)

Дамеуш Максустовна Ескендирова — кандидат технических наук, ассоциированный профессор, заведующая кафедрой кибербезопасности Международного университета информационных технологий (Казахстан)

Ниязгулова Айгуль Аскарбековна — кандидат филологических наук, доцент, профессор, заведующая кафедрой медиакоммуникации и истории Казахстана Международного университета информационных технологий (Казахстан)

Айтмаганбетов Алтай Зуфарович — кандидат технических наук, профессор кафедры радиотехники, электроники и телекоммуникаций Международного университета информационных технологий (Казахстан)

Бахтиярова Елена Ажибековна — кандидат технических наук, ассоциированный профессор, заведующая кафедрой радиотехники, электроники и телекоммуникаций Международного университета информационных технологий (Казахстан)

Канибек Сансызбай — PhD, ассоциированный профессор, профессор-исследователь кафедры кибербезопасности, Международного университета информационных технологий (Казахстан)

Тынымбаев Сахиябай — кандидат технических наук, профессор, профессор-исследователь кафедры компьютерной инженерии, Международного университета информационных технологий (Казахстан)

Алимсиреб Али Абд — PhD, ассоциированный профессор кафедры кибербезопасности Международного университета информационных технологий (Казахстан)

Мохамед Ахмед Хамада — PhD, ассоциированный профессор кафедры информационных систем Международного университета информационных технологий (Казахстан)

Янг Им Чу — PhD, профессор университета Гачон (Южная Корея)

Тадеуш Валлас — PhD, проректор университета имен Адама Мицкевича (Польша)

Мамырбаев Оркен Жумажанович — PhD, заместитель директора по науке РГП Института информационных и вычислительных технологий Комитета науки МНВО РК (Казахстан)

Бушуев Сергей Дмитриевич — доктор технических наук, профессор, директор Украинской ассоциации управления проектами «УКРНЕТ», заведующий кафедрой управления проектами Киевского национального университета строительства и архитектуры (Украина)

Белошицкая Светлана Васильевна — доктор технических наук, доцент, профессор кафедры вычислений и науки о данных Astana IT University (Казахстан)

ОТВЕТСТВЕННЫЙ РЕДАКТОР:

Мрзабаева Раушан Жалиевна — магистр, редактор Международного университета информационных технологий (Казахстан)

Международный журнал информационных и коммуникационных технологий

ISSN 2708–2032 (print)

ISSN 2708–2040 (online)

Префикс DOI: 10.54309

Периодичность: 4 выпусков в год.

Язык издания: казахский, русский, английский.

Тематическая направленность: "Информационные технологии"; "Информационная безопасность и коммуникационные технологии"; "Цифровые технологии в развитии социо-экономических систем".

Сайт журнала: <https://journal.iitu.edu.kz>

Распространение: материалы распространяются по лицензии Creative Commons Attribution 4.0

Собственник: АО «Международный университет информационных технологий» (г. Алматы).

Авторские права: © Международный журнал информационных и коммуникационных технологий, 2026

CONTENTS

DIGITAL TECHNOLOGIES IN THE DEVELOPMENT OF SOCIOECONOMIC SYSTEMS

A.B. Zhalgas, Y.N. Kalpakov, B.Ye. Amirgaliyev MACHINE LEARNING-DRIVEN OPTIMIZATION OF LOGISTICS IN SMART CITIES: A CASE STUDY OF ASTANA	11
L. Kurmangazyieva, Sh. Kodanova, M. Urazgaliyeva, O. Findik, S. Iskakova INTEGRATING FUZZY LOGIC AND ARTIFICIAL INTELLIGENCE IN OPTIMIZING BUSINESS PROCESS AUTOMATION DECISIONS	26
Y. Mailybayev, U. Adilbayeva, R. Amanova ORGANIZATION OF AN ONLINE SURVEY OF PARTICIPANTS IN THE EDUCATIONAL PROCESS AND ANALYSIS OF THE RESULTS BASED ON THE MODIFIED DELPHI METHOD	48
V.A. Takizhanov, A.Z. Ibragimov, A. Shalakhmetov SIMULATION-BASED ROBUSTNESS ASSESSMENT OF ASTANA'S BUS NETWORK UNDER RANDOM AND TARGETED FAILURES	63
G. Hamada, M. Hamada LEVERAGING MACHINE LEARNING MODELS TO BOOST THE MANIPULATION OF UNSTRUCTURED DECISIONS AND UNSTRUCTURED DATA IN DIGITAL BUSINESS FIRMS	78

INFORMATION TECHNOLOGY

M. Zh. Aitimov, G. K. Muratova, Zh. K. Bissenbayeva, I.M. Bapiyev, M. Kassim SEMANTIC COMPLETENESS IN KAZAKH-LANGUAGE EXTRACTIVE QA THROUGH ONTOLOGY AND RETRIEVAL MECHANISMS	96
A.Aitim, A. Auyezova ENCODING NP-COMPLETE PROBLEM INSTANCES INTO NATURAL LANGUAGE FOR LLM PROCESSING	109
O.N. Akylbekov, Y.T. Dauletbek, A.N. Moldagulova, G.S. Zakariya, D.A. Gura MACHINE LEARNING METHODS FOR ANALYSING THREE-DIMENSIONAL SPATIAL DATA IN KAZAKHSTAN'S LAND USE PLANNING	126
S.Zh. Aliaskarov, R.K. Uskenbayeva, A. Razaque, A.B. Kassymova, A.M. Anartayeva TOWARDS EFFICIENT BIG DATA ANALYTICS IN REGIONAL SYSTEMS: PRACTICAL INSIGHTS FROM HYBRID ARCHITECTURE DEPLOYMENT	146
Zh. Bilyalova, N. Shazhdekeyeva, K. Uteulyieva, T.Akhmurzina, L. Nurgaliyeva A MATHEMATICAL MODEL FOR DECISION-MAKING UNDER UNCERTAINTY HYBRID BASED ON FUZZY LOGIC AND GENERATIVE ARTIFICIAL INTELLIGENCE	165
A. Ismailova, G. Yessenbayeva, K. Kadyrkulov, R. Moldasheva, A. Amangeldi DEVELOPMENT OF A HYBRID DEEP LEARNING MODEL FOR MULTICLASS CLASSIFICATION OF MICROSCOPIC IMAGES OF BACTERIA	186
G. Kalman, J. Kultan, A.N. Ismukamova, N.M. Ausilova, Y.V. Makhatova A DOMAIN-KNOWLEDGE-BASED MODEL FOR REFERENCE RESOLUTION IN LOW-RESOURCE LANGUAGES.....	199
Y. Kamen, Zh. Yessendauletova, L. Fazylova, M. Rakhimzhanova, A.M. Nedzved USING NEURAL NETWORKS FOR OBJECTIVE ASSESSMENT OF ATTENTION IN CHILDREN BASED ON EEG DATA	216
A.Ye. Kulakayeva, Ye.A. Bakhtiyarova, G.T. Jakanova, Sh. Nursultan COMPARATIVE ANALYSIS OF VARIOUS RADIO WAVE PROPAGATION MODELS FOR MOBILE NETWORK COVERAGE PREDICTION	231
A. Kalykulova, K. Bakirov, A. Shoman, A. Nugumanova FORMATION OF A UNIFIED DATA SET FOR ANALYZING THE RELATIONSHIP BETWEEN DOG BREEDS AND DISEASES	247
D. Kantayeva, A. Seisenbekkyzy, S. Biloshchytska COMPARATIVE EVALUATION MODEL BASED ON EXPERT SYSTEMS FOR ABSTRACTIVE SUMMARIZATION OF SCIENTIFIC TEXTS	269
N. Mordvintsev, Zh. Oralbekova, A. Bakiyeva DEEP LEARNING-BASED VEHICLE MAKE AND MODEL RECOGNITION: DATASET CHALLENGES	

AND INFLUENCING FACTORS IN URBAN TRAFFIC	269
M.B. Nurpeissova, Sh.K. Aitkazinova, A.M. Abenov, N.S. Donenbayeva	
METHODOLOGY FOR TRANSFORMING SATELLITE COORDINATES INTO A TOPOCENTRIC RECTANGULAR COORDINATE SYSTEM	315
L. Naizabayeva, G. Turken, R.A. Druba	
EFFECTIVE METHOD FOR OPTIMAL CLUSTERING IN UNSUPERVISED LEARNING	328
S. Nurgaliyeva, Zh. Seitkaliyev, A. Sakhipov, M. Kali, R. Hrmo	
YIELD FORECASTING FOR FRUITS AND VEGETABLES USING RANDOM FOREST ON LARGE- SCALE AGROCLIMATIC DATA	339
A. Nurgalykov, S. Sapakova, D. Zhalmukhanbetov, G. Nurgazy, A. Myrzabayev	
LANGUAGE ASYMMETRY IN LLMS: THE IMPACT OF NON-ENGLISH DATA ON ACCURACY AND RELIABILITY	355
A. Ospanov, P. Alonso-Jordá, A. Zhumadillayeva	
BLOCKCHAIN-ENABLED ERP WAREHOUSE INTEGRATION WITH IOT DIMENSIONERS AND MACHINE LEARNING–OPTIMIZED DIMENSIONAL WEIGHT RECONCILIATION	371
A.A. Sakhipov, R.B. Seıitbek	
EVENT-DRIVEN MICROSERVICES FOR INCIDENT DETECTION AND RESPONSE IN INTELLIGENT TRAFFIC SYSTEM	387
A. Tursynova, B. Omarov	
EVOLUTION OF THE EFFECTIVENESS OF CONDITIONAL GAN FOR THE SYNTHESIS OF CT IMAGES OF THE BRAIN IN THE DIAGNOSIS OF STROKE	400
G. Yusupova, K.S. Shadinova, D. Ussipbekova, Zh.Zh. Azhibekova, P. Schmidt	
DETERMINATION OF SOIL PROFILE STRATIFICATION AT 0–200 CM DEPTH USING A MULTILEVEL STACKING MODEL	414

INFORMATION SECURITY AND COMMUNICATION TECHNOLOGIES

S.A. Adilzhanova, M.Zh. Sakypbekova, L.Sh. Cherikbaeva, G.A. Tyulepberdinova, G.T. Zhubanysheva	
SYSTEMATIC ANALYSIS OF RISK ASSESSMENT METHODS AND MODELS IN INFORMATION SECURITY.....	427
T. K. Zhukabayeva, D.B. Baumuratova, E. Benkhelifa , N.A. Niyetbayeva	
EDGE COMPUTING-BASED TECHNIQUE FOR CONSTRUCTION OF ATTACK DETECTION MEANS IN CYBER-PHYSICAL SYSTEMS OF INDUSTRIAL INTERNET-OF-THINGS	453
N.E. Karabayev, S.K. Serikbayeva, Y.M. Mardenov, B. Tassuov, M. Fajkus	
DETECTION OF CYBER ATTACKS IN TRANSPORT NETWORKS BASED ON MACHINE LEARNING METHODS	475
B.A. Kumalakov, A.O. Dargulova	
A HYBRID FRAMEWORK FOR RESUME-JOB MATCHING SYSTEM	494
V. Makhatova, B. Dzhugembayeva, A. Gabdulova, L. Nurgaliyeva, A. Abdigaliyeva	
MATHEMATICAL MODEL FOR OPTIMAL SENSOR SELECTION IN SIEM SYSTEMS USING THE ANALYTIC HIERARCHY PROCESS	509

МАЗМУНЫ

ӘЛЕУМЕТТІК-ЭКОНОМИКАЛЫҚ ЖҮЙЕЛЕРДІ ДАМУДАҒЫ ЦИФРЛЫҚ ТЕХНОЛОГИЯЛАР

А.Б. Жалғас, Е.Н. Калпаков, Б.Е. Амиргалиев	
АҚЫЛДЫ ҚАЛАЛАРДАҒЫ ЛОГИСТИКАНЫ МАШИНАЛЫҚ ОҚЫТУҒА НЕГІЗДЕЛГЕН ОҢТАЙЛАНДЫРУ: АСТАНАНЫҢ ЖАҒДАЙЫН ЗЕРТТЕУ.....	11
Л.Қурманғазиева, Ш. Қоданова, М. Уразғалиева, О. Findik, С. Искакова	
ЖАСАНДЫ ИНТЕЛЛЕКТ ПЕН АЙҚЫН ЕМЕС ЛОГИКАНЫ БІРІКТІРУ АРҚЫЛЫ БИЗНЕС- ПРОЦЕСТЕРДІ АВТОМАТТАНДЫРУ ШЕШІМДЕРІН ОҢТАЙЛАНДЫРУ	26
Е. Майлыбаев, У. Адилбаева, Р. Аманова	
ҰЙЫМДАСТЫРЫЛҒАН ОНЛАЙН САУАЛНАМА АРҚЫЛЫ БІЛІМ БЕРУ ПРОЦЕСІНЕ ҚАТЫСУШЫЛАРДЫҢ ПІКІРЛЕРІН ЖИНАУ ЖӘНЕ НӘТИЖЕЛЕРІН МОДИФИКАЦИЯЛАНҒАН ДЕЛЬФИ ӘДІСІ НЕГІЗІНДЕ ТАЛДАУ	48
В.А. Такижанов, А.Ж. Ибрагимов, А. Шалахметов	

МОДЕЛЬДЕУ НЕГІЗІНДЕ АСТАНАНЫҢ АВТОБУС ЖЕЛІСІНІҢ ТҰРАҚТЫЛЫҒЫН БАҒАЛАУ: КЕЗДЕЙСОҚ ЖӘНЕ МАҚСАТТЫ ІСТЕН ШЫҒУЛАР ЖАҒДАЙЫНДА	63
Г. Хамада, М. Хамада ЦИФРЛЫҚ БИЗНЕС-ҰЙЫМДАРЫНДА ҚҰРЫЛЫМДАЛМАҒАН ШЕШІМДЕР МЕН ҚҰРЫЛЫМДАЛ- МАҒАН ДЕРЕКТЕРМЕН ЖҰМЫС ІСТЕУ ТИІМДІЛІГІН АРТТЫРУ ҮШІН МАШИНАЛЫҚ ОҚЫТУ МОДЕЛЬДЕРІН ПАЙДАЛАҢУ	78

АҚПАРАТТЫҚ ТЕХНОЛОГИЯЛАР

М.Ж. Айтимов, Г.К. Муратова, Ж.К. Бисенбаева, И.М. Бапиев, М. Кассим ОНТОЛОГИЯ ЖӘНЕ ІЗДЕУ МЕХАНИЗМДЕРІ АРҚЫЛЫ ҚАЗАҚ ТІЛІНДЕГІ ЭКСТРАКЦИЯЛЫҚ ҚА-ДАҒЫ СЕМАНТИКАЛЫҚ ТОЛЫҚТЫҚ	96
Ә. Әйтiм, Ә. Әуезова LLM ӨНДЕУІ ҮШІН NP-ТОЛЫҚ ЕСЕПТЕРДІҢ ЭКЗЕМПЛЯРЛАРЫН ТАБИҒИ ТІЛДЕ КОДТАУ	109
О.Н. Ақылбеков, Е.Т. Даулетбек, А.Н. Молдагулова, Г.С. Закария, Д.А. Гура ҚАЗАҚСТАННЫҢ АУМАҚТЫҚ ЖОСПАРЛАУЫНДАҒЫ ҮШ ӨЛШЕМДІ КЕҢІСТІКТІК МӘЛІМЕТТЕРДІ ТАЛДАУ ҮШІН МАШИНАЛЫҚ ОҚЫТУ ӘДІСТЕРІ	126
С.Ж. Алиаскаров, Р.К. Ускенбаева, А. Разак, А.Б. Касымова, А.М. Анартаева АЙМАҚТЫҚ ЖҮЙЕЛЕРДЕГІ ҮЛКЕН ДЕРЕКТЕРДІ ТИІМДІ ТАЛДАУҒА ҚАРАЙ: ГИБРИДТІ АРХИТЕКТУРАНЫ ЕНГІЗУДІҢ ПРАКТИКАЛЫҚ ТҮСІНІКТЕР.....	146
Ж. Билялова, Н. Шаждекеева, К. Өтеулиева, Т. Ахмурзина, Л. Нұрғалиева АЙҚЫН ЕМЕС ЛОГИКА ЖӘНЕ ГЕНЕРАТИВТІ ЖАСАНДЫ ИНТЕЛЛЕКТ НЕГІЗІНДЕ БЕЛГІСІЗДІК ЖАҒДАЙЫНДА ШЕШІМ ҚАБЫЛДАУДЫҢ ГИБРИДТІ МАТЕМАТИКАЛЫҚ МОДЕЛІ	165
А.А. Исмаилова, Г.Р. Есенбаева, К.К. Кадиркулов, Р.Н. Молдашева, А. Амангелді РОСКОПИЯЛЫҚ БЕЙНЕЛЕРІН КӨПКЛАССТЫ ЖІКТЕУГЕ АРНАЛҒАН ГИБРИДТІ ТЕРЕҢ ОҚЫТУ МОДЕЛІН ӨЗІРЛЕУ	186
Г. Қалман, К. Ярослав, А.Н. Исмуканова, Н.М. Аусилова, В.Е. Махатова ПӘНДІК САЛА БІЛІМ НЕГІЗІНДЕ РЕУСРСТАРЫ АЗ ТІЛДЕРДЕГІ РЕФЕРЕНЦИЯНЫ ШЕШУДІҢ МОДЕЛІ.....	199
Е.Г. Кәмен, Ж.Т. Есендаулетова, Л.С. Фазылова, М.Б. Рахимжанова, А.М. Недзьведь ЭЭГ ДЕРЕКТЕРІ БОЙЫНША БАЛАЛАРДЫҢ ЗЕЙІНІН ОБЪЕКТИВТІ БАҒАЛАУ ҮШІН НЕЙРОНДЫҚ ЖЕЛІЛЕРДІ ҚОЛДАНУ	216
А.Е. Кулакаева, Е.А. Бахтиярова, Г.Т. Джаканова, Ш. Нурсултан ҰЯЛЫ БАЙЛАНЫС ЖЕЛІЛЕРІНІҢ ҚАМТУ АЙМАҒЫН БОЛЖАУҒА АРНАЛҒАН ӨРТҮРЛІ РАДИОТӨЛҚЫН ТАРАЛУ МОДЕЛЬДЕРІНІҢ САЛЫСТЫРМАЛЫ ТАЛДАУЫ	231
А. Калыкулова, К. Бакиров, А. Шоман, А. Нугуманова ИТ ТҰҚЫМДАРЫ МЕН АУРУЛАРЫ АРАСЫНДАҒЫ БАЙЛАНЫСТЫ ТАЛДАУҒА АРНАЛҒАН БЫРЫҒАЙ ДЕРЕКТЕР ЖИЫНТЫҒЫН ҚАЛЫПТАСТЫРУ	247
Д. Кантаева, А. Сейсенбекқызы, С. Билощницкая ҒЫЛЫМИ МӘТІНДЕРДІ АБСТРАКТИВТІ РЕФЕРАТТАУҒА АРНАЛҒАН ЭКСПЕРТТІК ЖҮЙЕЛЕРГЕ НЕГІЗДЕЛГЕН САЛЫСТЫРМАЛЫ БАҒАЛАУ МОДЕЛІ	269
Н. Мордвинцев, Ж. Оралбекова, А. Бакиева ТЕРЕҢ ОҚЫТУҒА НЕГІЗДЕЛГЕН КӨЛІК ҚҰРАЛДАРЫНЫҢ МАРКАСЫ МЕН МОДЕЛІН ТАҢУ: ҚА- ЛАЛЫҚ КӨЛІК ҚОЗҒАЛЫСЫНДАҒЫ ДЕРЕКТЕР ЖИЫНТЫҒЫНЫҢ МӘСЕЛЕЛЕРІ ЖӘНЕ ЫҚПАЛ ЕТУШІ ФАКТОРЛАР	285
М.Б. Нұрпейісова, Ш.Қ. Айтқазина, А.М. Абен, Н.С. Дөненбаева СПУТНИКТІК КООРДИНАТТАРДЫ ТОПОЦЕНТРЛІК ТІК БҰРЫШТЫ КООРДИНАТТАР ЖҮЙЕСІНЕ ТҮРЛЕНДІРУДІҢ ӘДІСТЕМЕСІ	315
Л. Найзабаева, Г. Түркен, Р.А. Друба БАҚЫЛАНБАЙТЫН ОҚЫТУДАҒЫ ОҢТАЙЛЫ КЛАСТЕРЛЕУДІҢ ТИІМДІ ӘДІСІ	328
С. Нұрғалиева, Ж. Сенткалиев, А. Сахипов, М. Кали, Р. Грмо ҮЛКЕН КӨЛЕМДЕГІ АГРОКЛИМАТТЫҚ ДЕРЕКТЕР НЕГІЗІНДЕ RANDOM FOREST ӘДІСІН ПАЙДАЛАНА ОТЫРЫП, ЖЕМІС-КӨКӨНІС ДАҚЫЛДАРЫНЫҢ ӨНІМДІЛІГІН БОЛЖАУ	339
А. Нұрғалықов, С. Сапакова, Д. Жалмұханбетов, Г. Нұрғазы, А. Мырзабаев ҮЛКЕН ТІЛДІК МОДЕЛЬДЕРДЕГІ ТІЛДІК АСИММЕТРИЯ: АҒЫЛШЫН ТІЛІНЕН БАСҚА ДЕРЕКТЕРДІҢ ДӘЛДІК ПЕН СЕНІМДІЛІККЕ ӘСЕРІ	355
А. Оспанов, П. Алонсо-Хорда, А. Жұмаділлаева	

БЛОКЧЕЙН-ТЕХНОЛОГИЯСЫМЕН ЫҚПАЛДАС ERP ҚОЙМА ЖҮЙЕСІН ІОТ ДИМЕНСИОНЕРЛЕР ЖӘНЕ МАШИНАЛЫҚ ОҚЫТУ АРҚЫЛЫ ОПТИМИЗАЦИЯЛАНҒАН ӨЛШЕМДІ САЛМАҚ ЕСЕПТЕУМЕН ИНТЕГРАЦИЯЛАУ	371
А.А. Сахипов, Р.Б. Сейітбек ОҚИҒАҒА БАҒДАРЛАНҒАН МИКРОҚЫЗМЕТТЕР ЖҮЙЕСІ АРҚЫЛЫ АҚЫЛДЫ ТРАФИК ЖҮЙЕЛЕРІНДЕ ОҚИҒАЛАРДЫ АНЫҚТАУ ЖӘНЕ ШАРАЛАР ҚОЛДАНУ	387
А. Турсынова, Б. Омаров ИНСУЛЬТТИ ДИАГНОСТИКАЛАУ КЕЗІНДЕ МИ КТ-БЕЙНЕЛЕРІН СИНТЕЗДЕУГЕ АРНАЛҒАН ШАРТТЫ ҒАН ТИІМДІЛІГІНІҢ ЭВОЛЮЦИЯСЫ	400
Г.М. Юсупова, К.С. Шадинова, Д.И. Усипбекова, Ж.Ж. Ажибекова, Р. Schmidt ТОПЫРАҚ ПРОФИЛІНІҢ 0–200 СМ ТЕРЕНДІКТЕГІ СТРАТИФИКАЦИЯСЫН КӨПДЕНГЕЙЛІ СТЕКИНГ-МОДЕЛІМЕН АНЫҚТАУ.....	414

АҚПАРАТТЫҚ ҚАУІПСІЗДІК ЖӘНЕ КОММУНИКАЦИЯЛЫҚ ТЕХНОЛОГИЯЛАРҒА АРНАЛҒАН

С.А. Адилжанова, М.Ж. Сақыпбекова, Л.Ш. Черикбаева, Г.А. Түлепбердинова, Г.Т. Жубанышева АҚПАРАТТЫҚ ҚАУІПСІЗДІКТЕ ТӘУЕКЕЛДЕРДІ БАҒАЛАУ ӘДІСТЕРІ МЕН МОДЕЛЬДЕРІН ЖҮЙЕЛІ ТАЛДАУ.....	427
Т.К. Жукабаева, Д. Б. Баумуратова, Е. Бенкхелифа, Н.А. Ниетбаева ШЕКАРАЛЫҚ ЕСЕПТЕУЛЕРДІ ҚОЛДАНА ОТЫРЫП, ЗАТТАРДЫҢ ӨНЕРКӘСІПТІК ИНТЕРНЕТІНІҢ КИБЕРФИЗИКАЛЫҚ ЖҮЙЕЛЕРІНДЕГІ ШАБУЫЛДАРДЫ АНЫҚТАУ ҚҰРАЛДАРЫН ҚҰРУ ӘДІСТЕМЕСІ.....	453
Н.Е. Қарабаев, С.К. Серикбаева, Е.М. Марденов, Б. Тасуов, М. Файқус МАШИНАЛЫҚ ОҚЫТУ ӘДІСТЕРІНЕ НЕГІЗДЕЛГЕН КӨЛІК ЖЕЛІЛЕРІНДЕГІ КИБЕРШАБУЫЛДАРДЫ АНЫҚТАУ	475
Б.А. Кумалаков, А.О. Даргулова ТҮЙІНДЕМЕЛЕР МЕН ВАКАНСИЯЛАРДЫ АВТОМАТТАНДЫРЫЛҒАН СӘЙКЕСТЕНДІРУГЕ НЕГІЗДЕЛГЕН ГИБРИДТІ ҮМІТКЕРЛЕРДІ ІРІКТЕУ ЖҮЙЕСІ	494
В. Махатова, Б. Джугембаева, А. Габдулова, Л. Нургалиева, А. Абдигалиева ИЕРАРХИЯЛАРДЫ ТАЛДАУ ӘДІСІ НЕГІЗІНДЕ SIEM ЖҮЙЕЛЕРІНДЕ ОҢТАЙЛЫ СЕНСОРДЫ ТАҢДАУДЫҢ МАТЕМАТИКАЛЫҚ МОДЕЛІ	509

СОДЕРЖАНИЕ ЦИФРОВЫЕ ТЕХНОЛОГИИ В РАЗВИТИИ СОЦИО-ЭКОНОМИЧЕСКИХ СИСТЕМ

А.Б. Жалғас, Е.Н. Калпаков, Б.Е. Амиргалиев ОПТИМИЗАЦИЯ ЛОГИСТИКИ В УМНЫХ ГОРОДАХ НА ОСНОВЕ МАШИННОГО ОБУЧЕНИЯ: НА ПРИМЕРЕ АСТАНЫ	11
Л. Курмангазиева, Ш. Коданова, М. Уразгалиева, О. Финдик, С. Исакова ИНТЕГРАЦИЯ НЕЧЕТКОЙ ЛОГИКИ И ИСКУССТВЕННОГО ИНТЕЛЛЕКТА ПРИ ОПТИМИЗАЦИИ РЕШЕНИЙ ПО АВТОМАТИЗАЦИИ БИЗНЕС-ПРОЦЕССОВ	26
Е. Майлыбаев, У. Адилбаева, Р. Аманова СБОР МНЕНИЙ УЧАСТНИКОВ ОБРАЗОВАТЕЛЬНОГО ПРОЦЕССА ПОСРЕДСТВОМ ОРГАНИЗОВАННОГО ОНЛАЙН-АНКЕТИРОВАНИЯ И АНАЛИЗ РЕЗУЛЬТАТОВ НА ОСНОВЕ МОДИФИЦИРОВАННОГО МЕТОДА ДЕЛЬФИ	48
В.А. Такижанов, А.Ж. Ибрагимов, А. Шалахметов ОЦЕНКА УСТОЙЧИВОСТИ АВТОБУСНОЙ СЕТИ АСТАНЫ НА ОСНОВЕ МОДЕЛИРОВАНИЯ ПРИ СЛУЧАЙНЫХ И ЦЕЛЕНАПРАВЛЕННЫХ ОТКАЗАХ	63
Г. Хамада, М. Хамада ИСПОЛЬЗОВАНИЕ МОДЕЛЕЙ МАШИННОГО ОБУЧЕНИЯ ДЛЯ ПОВЫШЕНИЯ ЭФФЕКТИВНОСТИ РАБОТЫ С НЕСТРУКТУРИРОВАННЫМИ РЕШЕНИЯМИ И НЕСТРУКТУРИРОВАННЫМИ ДАННЫМИ В ЦИФРОВЫХ БИЗНЕС-ОРГАНИЗАЦИЯХ	78

ИНФОРМАЦИОННЫЕ ТЕХНОЛОГИИ

М.Ж. Айтимов, Г.К. Муратова, Ж.К. Бисенбаева, И.М. Бапиев, М. Кассим

СЕМАНТИЧЕСКАЯ ПОЛНОТА В КАЗАХСКОЯЗЫЧНОМ EXTRACTIVE QA ЧЕРЕЗ ОНТОЛОГИЮ И RETRIEVAL-МЕХАНИЗМЫ	96
А. Айтим, А. Ауезова КОДИРОВАНИЕ ЭКЗЕМПЛЯРОВ NP-ПОЛНЫХ ЗАДАЧ В ЕСТЕСТВЕННОМ ЯЗЫКЕ ДЛЯ ОБРАБОТКИ LLM	109
О.Н. Акылбеков, Е.Т. Даулетбек, А.Н. Молдагулова, Г.С. Закария, Д.А. Гура МЕТОДЫ МАШИННОГО ОБУЧЕНИЯ ДЛЯ АНАЛИЗА ТРЁХМЕРНЫХ ПРОСТРАНСТВЕННЫХ ДАННЫХ В ТЕРРИТОРИАЛЬНОМ ПЛАНИРОВАНИИ КАЗАХСТАНА	126
С.Ж. Алиаскаров, Р.К. Ускенбаева, А. Разак, А.Б. Касымова, А.М. Анартаева НА ПУТИ К ЭФФЕКТИВНОЙ АНАЛИТИКЕ БОЛЬШИХ ДАННЫХ В РЕГИОНАЛЬНЫХ СИСТЕМАХ: ПРАКТИЧЕСКИЕ ВЫВОДЫ ИЗ ВНЕДРЕНИЯ ГИБРИДНОЙ АРХИТЕКТУРЫ	146
Ж. Билялова, Н. Шаждекеева, К. Утеулиева, Т. Ахмурзина, Л. Нурғалиева ГИБРИДНАЯ МАТЕМАТИЧЕСКАЯ МОДЕЛЬ ПРИНЯТИЯ РЕШЕНИЙ В УСЛОВИЯХ НЕОПРЕДЕЛЕННОСТИ НА ОСНОВЕ НЕЧЕТКОЙ ЛОГИКИ И ГЕНЕРАТИВНОГО ИСКУССТВЕННОГО ИНТЕЛЛЕКТА	165
А.А. Исмаилова, Г.Р. Есенбаева, К.К. Кадиркулов, Р.Н. Молдашева, А. Амангелды РАЗРАБОТКА ГИБРИДНОЙ МОДЕЛИ ГЛУБОКОГО ОБУЧЕНИЯ ДЛЯ МНОГОКЛАССОВОЙ КЛАССИФИКАЦИИ МИКРОСКОПИЧЕСКИХ ИЗОБРАЖЕНИЙ БАКТЕРИЙ	186
Г. Калман, К. Ярослав, А.Н. Исмуханова, Н.М. Аусилова, В.Е. Махатова МОДЕЛЬ НА ОСНОВЕ ЗНАНИЙ ПРЕДМЕТНОЙ ОБЛАСТИ ДЛЯ РАЗРЕШЕНИЯ КОРЕФЕРЕНЦИИ В МАЛОРЕСУРСНЫХ ЯЗЫКАХ	199
Е.Г. Камен, Ж.Т. Есендаулетова, Л.С. Фазылова, М.Б. Рахимжанова, А.М. Недзведь ИСПОЛЬЗОВАНИЕ НЕЙРОННЫХ СЕТЕЙ ДЛЯ ОБЪЕКТИВНОЙ ОЦЕНКИ ВНИМАНИЯ У ДЕТЕЙ ПО ДАННЫМ ЭЭГ	216
А.Е. Кулакаева, Е.А. Бахтиярова, Г.Т. Джаканова, Ш. Нурсултан СРАВНИТЕЛЬНЫЙ АНАЛИЗ РАЗЛИЧНЫХ МОДЕЛЕЙ РАСПРОСТРАНЕНИЯ РАДИОВОЛН ДЛЯ ПРОГНОЗИРОВАНИЯ ПОКРЫТИЯ СЕТЕЙ МОБИЛЬНОЙ СВЯЗИ	231
А. Калыкулова, К. Бакиров, А. Шоман, А. Нугуманова ФОРМИРОВАНИЕ ЕДИНОГО НАБОРА ДАННЫХ ДЛЯ АНАЛИЗА ВЗАИМОСВЯЗИ МЕЖДУ ПОРОДАМИ СОБАК И ЗАБОЛЕВАНИЯМИ	247
Д. Кантаева, А. Сейсенбеккызы, С. Билощицкая СРАВНИТЕЛЬНАЯ МОДЕЛЬ ОЦЕНКИ НА ОСНОВЕ ЭКСПЕРТНЫХ СИСТЕМ ДЛЯ АБСТРАКТИВНОГО РЕФЕРИРОВАНИЯ НАУЧНЫХ ТЕКСТОВ	269
Н. Мордвинцев, Ж. Оралбекова, А. Бакиева РАСПОЗНАВАНИЕ МАРКИ И МОДЕЛИ ТРАНСПОРТНЫХ СРЕДСТВ НА ОСНОВЕ ГЛУБОКОГО ОБУЧЕНИЯ: ПРОБЛЕМЫ НАБОРОВ ДАННЫХ И ФАКТОРЫ, ВЛИЯЮЩИЕ НА РАБОТУ СИСТЕМЫ В УСЛОВИЯХ ГОРОДСКОГО ДВИЖЕНИЯ	285
М.Б. Нурпеисова, Ш.К. Айтказинова, А.М. Абенов, Н.С. Доненбаева МЕТОДИКА ПРЕОБРАЗОВАНИЯ СПУТНИКОВЫХ КООРДИНАТ В ТОПОЦЕНТРИЧЕСКУЮ ПРЯМОУГОЛЬНУЮ СИСТЕМУ КООРДИНАТ	315
Л. Найзабаева, Г. Туркен, Р.А. Друба ЭФФЕКТИВНЫЙ МЕТОД ОПТИМАЛЬНОЙ КЛАСТЕРИЗАЦИИ В ОБУЧЕНИИ БЕЗ УЧИТЕЛЯ	328
С. Нурғалиева, Ж. Сенткалиев, А. Сахипов, М. Кали, Р. Грмо ПРОГНОЗИРОВАНИЕ УРОЖАЙНОСТИ ФРУКТОВ И ОВОЩЕЙ С ИСПОЛЬЗОВАНИЕМ RANDOM FOREST НА ОСНОВЕ КРУПНОМАСШТАБНЫХ АГРОКЛИМАТИЧЕСКИХ ДАННЫХ	339
А. Нурғалыков, С. Сапакова, Д. Жалмуханбетов, Г. Нургазы, А. Мырзабаев ЯЗЫКОВАЯ АСИММЕТРИЯ В БОЛЬШИХ ЯЗЫКОВЫХ МОДЕЛЯХ: ВЛИЯНИЕ ДАННЫХ НА НЕАНГЛИЙСКИХ ЯЗЫКАХ НА ТОЧНОСТЬ И НАДЕЖНОСТЬ	355
А. Оспанов, П. Алонсо-Хорда, А. Жумадилаева ИНТЕГРАЦИЯ СКЛАДСКИХ МОДУЛЕЙ ERP-СИСТЕМ С ИСПОЛЬЗОВАНИЕМ БЛОКЧЕЙНА, ИОТ-ДИМЕНСИОНЕРОВ И ОПТИМИЗИРОВАННОГО МАШИНЫМ ОБУЧЕНИЕМ РАСЧЁТА ГАБАРИТНОГО ВЕСА	371
А.А. Сахипов, Р.Б. Сейитбек СОБЫТИЯ-ОРИЕНТИРОВАННЫЕ МИКРОСЕРВИСЫ ДЛЯ ОБНАРУЖЕНИЯ И РЕАГИРОВАНИЯ НА ИНЦИДЕНТЫ В ИНТЕЛЛЕКТУАЛЬНЫХ ТРАНСПОРТНЫХ СИСТЕМАХ	387
А. Тұрсынова, Б. Омаров ЭВОЛЮЦИЯ ЭФФЕКТИВНОСТИ УСЛОВНОГО GAN ДЛЯ СИНТЕЗА КТ-ИЗОБРАЖЕНИЙ ГОЛОВНО-	

ГО МОЗГА ПРИ ДИАГНОСТИКЕ ИНСУЛЬТА	400
Г.М. Юсупова, К.С. Шадинова, Д.И. Усипбекова, Ж.Ж. Ажибекова, П. Шмидт	
ОПРЕДЕЛЕНИЕ СТРАТИФИКАЦИИ ПОЧВЕННОГО ПРОФИЛЯ НА ГЛУБИНЕ 0–200 СМ С ИСПОЛЬЗОВАНИЕМ МОДЕЛИ МНОГОУРОВНЕВОГО НАЛОЖЕНИЯ	414

ИНФОРМАЦИОННАЯ БЕЗОПАСНОСТЬ И КОММУНИКАЦИОННЫЕ ТЕХНОЛОГИИ

С.А. Адилжанова, М.Ж. Сакыпбекова, Л.Ш. Черикбаева, Г.А. Тюлепбердинова, Г.Т. Жубанышева	
СИСТЕМАТИЧЕСКИЙ АНАЛИЗ МЕТОДОВ И МОДЕЛЕЙ ОЦЕНКИ РИСКОВ ИНФОРМАЦИОННОЙ БЕЗОПАСНОСТИ	427
Т.К. Жукабаева, Д.Б. Баумуратова, Е. Бенкхелифа, Н.А. Ниембаева	
МЕТОДИКА ПОСТРОЕНИЯ СРЕДСТВ ОБНАРУЖЕНИЯ АТАК В КИБЕРФИЗИЧЕСКИХ СИСТЕМАХ ПРОМЫШЛЕННОГО ИНТЕРНЕТА ВЕЩЕЙ С ИСПОЛЬЗОВАНИЕМ ГРАНИЧНЫХ ВЫЧИСЛЕНИЙ	453
Н.Е. Карабаев, С.К. Серикбаева, Е.М. Марденов, Б. Тасуов, М. Файкус	
ОБНАРУЖЕНИЕ КИБЕРАТАК В ТРАНСПОРТНЫХ СЕТЯХ НА ОСНОВЕ МЕТОДОВ МАШИННОГО ОБУЧЕНИЯ	475
Б.А. Кумалаков, А.О. Даргулова	
ГИБРИДНЫЙ ПОДХОД К АВТОМАТИЗИРОВАННОМУ ПОДБОРУ КАНДИДАТОВ НА ОСНОВЕ СОПОСТАВЛЕНИЯ РЕЗЮМЕ И ВАКАНСИЙ	494
В. Махатова, Б. Джугембаева, А. Габдулова, Л. Нургалиева, А. Абдигалиева	
МАТЕМАТИЧЕСКАЯ МОДЕЛЬ ВЫБОРА ОПТИМАЛЬНОГО СЕНСОРА В SIEM-СИСТЕМАХ СРЕДСТВАМИ МЕТОДА АНАЛИЗА ИЕРАРХИЙ	509

INTERNATIONAL JOURNAL OF INFORMATION AND COMMUNICATION TECHNOLOGIES

ISSN 2708–2032 (print)

ISSN 2708–2040 (online)

Vol. 7. Is.1. Number 25 (2026). Pp. 285–314

Journal homepage: <https://journal.iitu.edu.kz>

<https://doi.org/10.54309/IJICT.2026.25.1.017>

DEEP LEARNING-BASED VEHICLE MAKE AND MODEL RECOGNITION: DATASET CHALLENGES AND INFLUENCING FACTORS IN URBAN TRAFFIC

*N. Mordvintsev, Zh. Oralbekova, A. Bakiyeva**

Astana IT University, Astana, Kazakhstan.

E-mail: Zh.Oralbekova@astanait.edu.kz

Nikita Mordvintsev — Master's student, Astana IT University, Astana, Kazakhstan

<https://orcid.org/0009-0008-9112-6229>;

Zhanar Oralbekova — PhD, Associate Professor, Astana IT University, Astana, Kazakhstan

E-mail: Zh.Oralbekova@astanait.edu.kz, <https://orcid.org/0000-0002-3726-8882>;

Aigerim Bakiyeva — Candidate of Technical Sciences (PhD), Assistant Professor, Astana IT University, Astana, Kazakhstan

<https://orcid.org/0000-0001-7186-6408>.

© N. Mordvintsev, Z. Oralbekova, A. Bakiyeva

Abstract. This paper presents a deep learning-based approach to vehicle make and model recognition (VMMR). Using ResNet50, AlexNet, VGG19, MobileNet, EfficientNet, VIT b16, ConvNeXt, SimCLR, CLIP we address the challenges of annotation of data sets, class imbalance, and quality of real-world cameras. A data set of 283,899 vehicle images was extracted and tested, achieving validation accuracy of 0.07 to 0.32. We analyze how vehicle size, acceleration, and turning radius affect detection performance and propose directions for optimizing smart city traffic systems.

Keywords: Deep Learning, Vehicle Recognition, VMMR, ResNet50, Dataset Augmentation, Intelligent Transportation Systems, Urban Traffic, Model Classification, Smart Cities

For citation: Mordvintsev N., Oralbekova Z., Bakiyeva A. (2026). Deep learning-based vehicle make and model recognition: dataset challenges and influencing factors in urban traffic // International journal of information and communication technologies. Vol. 7. No. 26. Pp. 285–314. <https://doi.org/10.54309/IJICT.2026.26.2.017>. (In Eng.).

Conflict of interest: The authors declare that there is no conflict of interest.

ТЕРЕҢ ОҚЫТУҒА НЕГІЗДЕЛГЕН КӨЛІК ҚҰРАЛДАРЫНЫҢ
МАРКАСЫ МЕН МОДЕЛІН ТАҢУ: ҚАЛАЛЫҚ КӨЛІК



ҚОЗҒАЛЫСЫНДАҒЫ ДЕРЕКТЕР ЖИЫНТЫҒЫНЫҢ МӘСЕЛЕЛЕРІ ЖӘНЕ ЫҚПАЛ ЕТУШІ ФАКТОРЛАР

*Н. Мордвинцев, Ж. Оралбекова, А. Бакиева**

Astana IT University, Астана, Қазақстан.

E-mail: Zh.Oralbekova@astanait.edu.kz

Мордвинцев Никита — магистрант, Astana IT University, Астана, Қазақстан

<https://orcid.org/0009-0008-9112-6229>;

Оралбекова Жанар — PhD, қауымдастырылған профессор, Astana IT University, Астана, Қазақстан

E-mail: Zh.Oralbekova@astanait.edu.kz, <https://orcid.org/0000-0002-3726-8882>;

Бакиева Айгерим — техника ғылымдарының кандидаты, PhD, ассистент-профессор, Astana IT University, Астана, Қазақстан

<https://orcid.org/0000-0001-7186-6408>.

© Н. Мордвинцев, Ж. Оралбекова, А. Бакиева

Аннотация. Мақалада терең оқытуға негізделген көлік құралдарының маркасы мен моделін тану (Vehicle Make and Model Recognition, VMMR) тәсілі ұсынылады. ResNet50, AlexNet, VGG19, MobileNet, EfficientNet, ViT-B/16, ConvNeXt, SimCLR және CLIP модельдерін пайдалана отырып, деректер жиынтығын аннотациялау, сыныптар арасындағы теңгерімсіздік және нақты жағдайларда камералар арқылы алынған кескіндердің сапасы сияқты мәселелер қарастырылады. Көлік құралдарының 283 899 кескінінен тұратын деректер жиынтығы қалыптастырылып, тестіленді; валидациялық деректер жиынындағы дәлдік 0,07-ден 0,32-ге дейінгі аралықта болды. Көлік құралының өлшемі, үдеуі және бұрылу радиусы сияқты факторлардың тану тиімділігіне әсері талданып, ақылды қалалардың көлік жүйелерін оңтайландыру бағыттары ұсынылды.

Түйінді сөздер: терең оқыту, көлік құралдарын тану, VMMR, ResNet50, деректер жиынтығын аугментациялау, интеллектуалды көлік жүйелері, қалалық көлік қозғалысы, модельдерді жіктеу, ақылды қалалар

Дәйексөздер үшін: Мордвинцев Н., Оралбекова Ж., Бакиева А. (2026). Терең оқытуға негізделген көлік құралдарының маркасы мен моделін тану: қалалық көлік қозғалысындағы деректер жиынтығының мәселелері және ықпал етуші факторлар // халықаралық ақпараттық және коммуникациялық технологиялар журналы. Т. 7. No 25. Б. 285–314. <https://doi.org/10.54309/IJICT.2026.25.1.017>. (Ағыл. тіл.).

Мүдделер қақтығысы: Авторлар осы мақалада мүдделер қақтығысы жоқ деп мәлімдейді.

РАСПОЗНАВАНИЕ МАРКИ И МОДЕЛИ ТРАНСПОРТНЫХ СРЕДСТВ НА ОСНОВЕ ГЛУБОКОГО ОБУЧЕНИЯ: ПРОБЛЕМЫ НАБОРОВ ДАННЫХ



И ФАКТОРЫ, ВЛИЯЮЩИЕ НА РАБОТУ СИСТЕМЫ В УСЛОВИЯХ ГОРОДСКОГО ДВИЖЕНИЯ

*Н. Мордвинцев, Ж. Оралбекова, А. Бакиева**

Astana IT University, Астана, Казахстан.

E-mail: Zh.Oralbekova@astanait.edu.kz

Мордвинцев Никита — магистрант, Astana IT University, Астана, Казахстан
<https://orcid.org/0009-0008-9112-6229>;

Оралбекова Жанар — PhD, ассоциированный профессор, Astana IT University, Астана, Казахстан

E-mail: Zh.Oralbekova@astanait.edu.kz, <https://orcid.org/0000-0002-3726-8882>;

Бакиева Айгерим — К.т.н., PhD, Ассистент-профессор, Astana IT University, Астана, Казахстан
<https://orcid.org/0000-0001-7186-6408>.

© Н. Мордвинцев, Ж. Оралбекова, А. Бакиева

Аннотация. В статье представлен подход к распознаванию марки и модели транспортных средств (Vehicle Make and Model Recognition, VMMR) на основе глубокого обучения. С использованием моделей ResNet50, AlexNet, VGG19, MobileNet, EfficientNet, ViT-B/16, ConvNeXt, SimCLR и CLIP рассматриваются проблемы аннотирования наборов данных, дисбаланса классов и качества изображений, получаемых камерами в реальных условиях. Был сформирован и протестирован набор данных, содержащий 283 899 изображений транспортных средств; точность на валидационной выборке составила от 0,07 до 0,32. Проанализировано влияние размера транспортного средства, ускорения и радиуса поворота на эффективность распознавания, а также предложены направления оптимизации транспортных систем умного города.

Ключевые слова: глубокое обучение, распознавание транспортных средств, VMMR, ResNet50, аугментация набора данных, интеллектуальные транспортные системы, городской транспортный поток, классификация моделей, умные города

Для цитирования: Мордвинцев Н., Оралбекова Ж., Бакиева А. (2026). Распознавание марки и модели транспортных средств на основе глубокого обучения: проблемы наборов данных и факторы, влияющие на работу системы в условиях городского движения // Международный журнал информационных и коммуникационных технологий. Т. 7. No. 25. Стр. 285-314. <https://doi.org/10.54309/IJICT.2026.25.1.017>. (На англ.).

Конфликт интересов: авторы заявляют об отсутствии конфликта интересов.

Introduction.

Deep learning has become a fundamental approach for vehicle make and model recognition (VMMR) within intelligent transportation systems (ITS). Convolutional Neural Networks (CNNs) are widely employed to automatically extract hierarchical features from vehicle images, progressing from low-level visual cues to high-level semantic representations. Various architectures have been proposed to enhance VMMR performance, including semi-supervised CNNs, coarse-to-fine frameworks for fine-grained classification, and hybrid methods integrating dimensionality reduction techniques such as Principal Component Analysis (PCA) to accelerate training. These deep learning models ensure reliable recognition from multiple perspectives (Jabeen et al., 2021). Also current paper made comparison with more advanced models like MobileNet, EfficientNet and Vision Transformer VIT b16, ConvNeXt, SimCLR, CLIP. In deep learning, channel fusion methods play a vital role in improving model performance, mainly through concatenation, summation, and multiplication. Concatenation merges feature maps from different levels along the depth dimension, improving the model's ability to represent features. This is often used in encoder-decoder architectures where low- level and high-level features are combined.

An analyzed study shows that the ITS system includes dynamic data transfer, where the machine model definition will help to provide some data (Vahora et al., 2025). Conventional traffic monitoring systems depend largely on manual observation or basic sensor-based methods, which restrict their accuracy, coverage, and real-time responsiveness. The integration of Deep Learning (DL) and Computer Vision (CV) has emerged as an advanced approach for intelligent traffic surveillance, enabling automated, scalable, and adaptive systems capable of analyzing and responding to traffic situations in real time without human intervention (Siva et al., 2025). Intelligent traffic lights, smart parking guidance systems, and advanced public transportation technologies are employed to enhance traffic flow, alleviate congestion, and boost overall traffic efficiency. By leveraging the centralized learning and decentralized execution framework of the Actor- Critic strategy gradient algorithm, additional information is utilized by critics to streamline the traffic signal control process and achieve optimized traffic signal management (Wei et al., 2024). In the article of the analyzed research, the author includes queue length, average speed, and ambulance data in the system architecture. Deep learning on the semantic data of cars adds data on the model and type of car to the architectures, and therefore more detailed physical data on car models (Girhe et al., 2022). While several studies have applied deep learning to vehicle make and model recognition (VMMR), this research uniquely focuses on adapting and evaluating state-of-the-art CNN architectures (ResNet50, VGG19, AlexNet, MobileNet, EfficientNet, VIT b16, ConvNeXt, SimCLR, CLIP). By incorporating physical characteristics of vehicles (such as acceleration, size, and turning radius) into the analysis, this work provides a multi-dimensional framework that goes beyond image classification – aiming to support smart city traffic optimization efforts.

Materials and methods.

Building a deep learning system architecture component from camera data to

obtain data on traffic volume, car type, car brand, and hence subsequent aspects about each car and aggregated road line values. Maintaining and overcoming the difficulties of maintaining a deep learning model in the form of creating datasets.

How can deep learning techniques be applied to develop an accurate and efficient car brand detection system for traffic roads, and how can we create a reliable dataset using existing tools for training these models?

Objectives:

- Identifying the factors related to car models that influence city traffic and investigating these factors for specific brands through official vehicle documentation;
- Analyze modern approaches to data processing and analysis, focusing on existing methods and technologies for vehicle detection and identification;
- Train models on the identified datasets and evaluate their performance.

ResNet50 is a widely used deep learning model from the ResNet series, consisting of a structured arrangement of Bottleneck modules—specifically, 3, 4, 6, and 3 modules in its second to fifth layers, respectively. These modules include two distinct block types: Conv Blocks and Identity Blocks. Positioned between shallow and deep networks, ResNet50 balances model complexity and performance, making it well-suited for small-scale image datasets while reducing overfitting risks. While primarily designed for image classification, ResNet50's architecture can be further optimized for specialized tasks. For instance, enhancements such as a detail extraction module, which incorporates differential convolution for improved texture and contour recognition, can refine feature detection. Additionally, multi-channel fusion techniques, such as incorporating a binary mask, help the model focus on essential image regions, improving classification accuracy (Wang et al., 2022).

ResNet50 is a convolutional neural network architecture developed by researchers at Microsoft Research and introduced at the CVPR conference in 2015. It consists of 50 layers, with batch normalization applied after each convolution to ensure more stable and faster training. The network uses the ReLU (Rectified Linear Unit) activation function. Following the initial layer, a Max Pooling layer is applied to reduce the dimensionality of the data. At the end of the model, Global Average Pooling is used to reduce the number of parameters and prevent overfitting. ResNet50 is widely used for image classification, object detection, and segmentation tasks. In this work, a pre-trained ResNet50 model from torchvision.models was used, with the final layer replaced to predict one of 43 classes. The model was fine-tuned, freezing all layers except the last one. The CrossEntropyLoss function was used for training, with the Adam optimizer set at a learning rate of 0.001. The model was trained for 10 epochs (Sharma et al., 2023).

ResNet (Residual Network) is a deep convolutional neural network (CNN) architecture introduced by He et al. in 2015. It introduced residual learning, which uses skip connections (shortcuts) to bypass certain layers, addressing the vanishing gradient problem in very deep networks. This innovation allowed for the training of extremely deep networks, such as ResNet-50, ResNet-101, and ResNet-152, without performance degradation. ResNet achieved state-of-the-art results on the ImageNet

dataset, significantly improving classification accuracy (Elgendy, 2020).

ResNet introduced residual connections to address the vanishing gradient problem in deep networks, allowing for deeper and more accurate models. However, its complexity and depth can lead to increased computational costs and training time. Additionally, ResNet is known to be vulnerable to adversarial attacks and overfitting in small datasets if not properly regularized. Research by Li et al. (2022) highlights that Although ResNet reduces the issue of gradient vanishing, it is computationally intensive and may struggle to generalize to unconventional image distributions (Wang et al., 2022).

Hyperparameter tuning, particularly for learning rate, batch size, and the temperature value t is critical for enhancing the SupCon ResNet model's performance. In the referenced work, t was fixed at 0.07, while different combinations of learning rates and batch sizes were tested, revealing that a batch size of 512 with a learning rate of 0.05 achieved the lowest average false negative rate (FNR), outperforming larger batch sizes (Hoang et al., 2024). The Residual Neural Network (ResNet) architecture to address vanishing gradient issues in deep CNNs by using skip connections, enabling the training of very deep models like ResNet- 50 and ResNet-18 efficiently and with improved performance (Naaman, 2022). The ResNet-50 architecture, applied to vehicle brand detection as reported in the cited research, boosted classification accuracy from an initial 34 % to a final 95.31 %, highlighting its effectiveness in handling diverse vehicle scales and improving overall model performance (Mohite et al., 2025). The FastAI-driven ResNet-32 model demonstrated exceptional diagnostic performance in classifying ductal carcinoma tissue slides, achieving a classification confidence of 98.6 % and a high Diagnostic Odds Ratio (DOR) of 196.75 across multiple cross-validation folds (Praveen et al., 2022). Based on the reported results, the improved ResNet-18 model achieved the highest overall classification accuracy of 96.50 % on the MIT-BIH dataset, outperforming state-of- the-art models in ECG heartbeat classification, particularly by leveraging slicing techniques and compensating for class imbalance (Jing et al., 2021). Based on the results reported by author the iSPLInception model, built upon the Inception-ResNet architecture, outperformed CNN, CNN-LSTM, and LSTM variants across four UCI HAR datasets, demonstrating superior adaptability and scalability in human activity recognition despite dataset imbalances (Ronald et al., 2021). To improve ResNet-50 performance, Lin and Wu introduced adaptive learning rates and both L1/ L2 regularization to address overfitting and accuracy fluctuations. Additionally, by combining feature maps from intermediate layers (conv5 block1 out and conv5 block2 out), they enhanced the model's ability to detect critical patterns such as bleeding in diabetic retinopathy grading (Lin et al., 2023). The ResNet- 50 method achieves the highest overall accuracy (OA) due to its residual modules, which effectively solve the network degradation problem. The deep architecture, combined with convolutional layers, enhances feature extraction capabilities and training performance. ResNet-50's success is attributed to its ability to maintain robust performance even with deeper networks, setting it apart from other methods like BBO and CSO in this experiment.

Future work will explore different ResNet variants, such as Wide Residual Networks (WRN), ResNeXt, and MobileNet, to further investigate facial emotion recognition (Li et al., 2021). In the work cited by the authors, ResNet models, including ResNet-18 and ResNet-50, were applied to facial emotion recognition after preprocessing with CLAHE, using convolution, batch normalization, and residual blocks to effectively extract features and mitigate degradation in deep architectures (Sarwinda et al., 2021). Recent advancements in training procedures, as implemented in the timm library, have enhanced ResNet-50’s performance, offering improved training methods and data augmentations that contribute to better results compared to the original model (Wightman et al., 2021). Figure 1 shows ResNet model summary in this study.

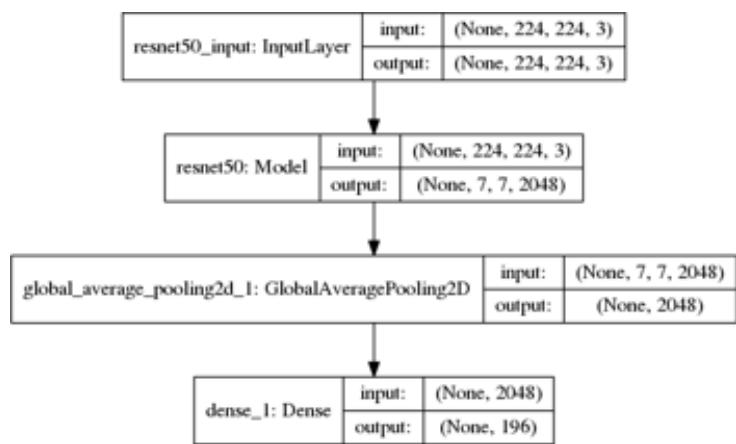


Fig. 1. Used pretrained ResNet model summary in this study.

VGG19

VGG19 is a deep convolutional neural network (CNN) developed by Simonyan and Zisserman as an extension of VGGNet. It consists of 19 weight layers, including 16 convolutional layers with 3×3 filters and three fully connected layers, followed by a softmax classifier. The network follows a uniform architecture, where small convolutional filters are stacked in multiple layers, increasing depth while maintaining a consistent structure. VGG19 improves upon AlexNet by using smaller 3×3 convolutional filters, which increase the network’s capacity to capture complex features while reducing the number of parameters per layer. Despite its greater depth and over 144 million parameters, VGG19 converges faster due to implicit regularization from its deeper structure. It achieved a top-5 error rate of approximately 7.4 % on the ImageNet dataset, making it more accurate than its predecessor, AlexNet (Elgendy, 2020).

VGG-19 is widely used for benchmarking due to its deep architecture, which enhances classification accuracy. It employs dropout layers to mitigate overfitting and max-pooling for downsampling. Compared to sigmoid activation, ReLU activation is used for efficient training and gradient stability. The model has been successfully applied in medical image classification, achieving 96% accuracy and 82% sensitivity on the Kaggle fundus image dataset (Sudha et al., 2020).

Sudha and Ganeshbabu (2020) noted that VGG19 suffers from high overfitting risk, especially on small or imbalanced datasets, which is a common issue in VMMR when car brands are unevenly represented (Sudha et al., 2020). Additionally, the lack of residual connections makes it harder for gradients to flow, and training can become unstable in deeper networks compared to ResNet.

The VGG19 model demonstrated excellent performance with a test accuracy of 97.51 % and a test loss of 0.06244, indicating accurate predictions and high classification effectiveness across the dataset (Chowdhury et al., 2024). VGG19, a deep convolutional neural network architecture, was used in referenced work with spatial attention and class balance techniques to achieve an accuracy of 97.38% for recognizing benign malware. Despite its high performance, the model faces challenges due to dataset imbalance, where some malware classes have significantly fewer examples than others (Awan et al., 2021). Based on the findings of the cited study, VGG-19 with transfer learning achieved an outstanding accuracy of 99.72 % for classifying tomato leaf diseases, utilizing HSV color space for image segmentation to improve classification performance. The model's superior results, including high precision, sensitivity, and F1 score, were achieved by effectively segmenting leaf regions and eliminating background, in contrast to previous methods that did not apply such preprocessing (Nguyen et al., 2022). The VGG-19 network offers significant advantages in image recognition, including high verification accuracy and efficient training and verification times due to its use of consistent 3x3 convolution kernels and a deeper network structure (Yang et al., 2021). In the article, VGG-16 and VGG-19 both show impressive performance across varying epoch numbers. VGG-16 achieves high accuracy on both training and test data, with a peak test accuracy of 0.9656 at epoch 1, while VGG-19 shows slightly better results, reaching a test accuracy of 0.9744 at epoch 15 and maintaining high performance throughout (Mascarenhas et al., 2021). In the discussion, the VGG- 19 model is used as the base architecture for the proposed model, with only the classifier layer being updated. Despite overfitting during training, careful tuning of hyperparameters helped improve the model's performance, though the FER2013 dataset showed lower accuracy compared to the other two datasets (Meena et al., 2022). The VGG-19 model applied for cataract detection achieved a test accuracy of 97.47 % on the Kaggle dataset, demonstrating its effectiveness in detecting cataracts from unfiltered fundus photographs. Despite this success, further research into feature extraction techniques and classification algorithms is needed for more in-depth and precise detection, including severity grading (Khan et al., 2021). The use of transfer learning with the VGG19 network for strip steel defect recognition is effective. The hierarchical learning rate adjustment, improved feature extraction module, and the Adam optimizer contribute to significant improvements in the model's accuracy, robustness, and convergence speed. The model's real-time performance is also competitive, with a detection speed of 54 images per second (Wan et al., 2021). In these results, VGG19 is used as a feature extraction method in the proposed algorithm, offering a nonlinear transformation approach, unlike the linear transformations (DWT, DCT, and DFT). This distinction highlights VGG19's ability to capture more complex, deep features for

medical image watermarking (Han et al., 2021). The VGG-19 model, when pretrained, demonstrated exceptional performance with an accuracy of 97.3 %, recall of 99.2 %, and precision of 96.7 %, making it highly effective for classifying pneumonia from chest X-ray images. The review article shows the good quality of the model in the analysis of medical images (Ikechukwu et al., 2021). Figure 2 shows the pretrained VGG19 model summary.

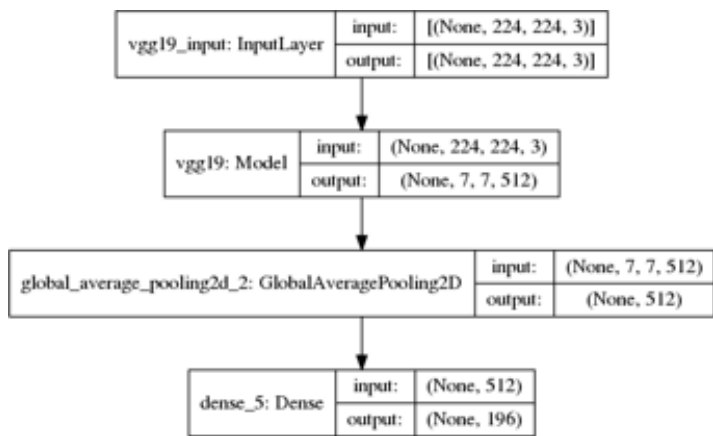


Fig. 2. Used pretrained VGG19 model summary in this study.

AlexNet is a deep neural network architecture developed in 2012 for image classification. It includes convolutional and pooling layers. The model uses activation, dropout, and overlapping pooling (ReLU) to reduce overfitting. AlexNet won the ImageNet competition (Li et al., 2021). AlexNet is a deep neural network that significantly improves computer vision, optimized for large-sized images. It was the winning model of the 2012 ImageNet Large Scale Visual Recognition Challenge (ILSVRC) and was developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. The architecture includes five convolutional layers with subsequent max-pooling layers, three fully connected layers, and a final softmax layer for classification. Unlike earlier models like LeNet, AlexNet incorporates Rectified Linear Unit (ReLU) activation functions to speed up training, dropout layers to reduce overfitting, and overlapping max pooling for improved feature extraction. Its depth and complexity, with approximately 60 million parameters and 650,000 neurons, enabled it to learn intricate patterns and significantly outperform previous approaches in image recognition tasks (Elgendy, 2020).

AlexNet, though revolutionary when introduced, is now considered relatively shallow and outdated for complex tasks like fine-grained vehicle classification. It has only eight layers and lacks the depth and modularity of newer architectures. AlexNet tends to underfit when applied to large scale, high resolution datasets and does not include advanced mechanisms for extracting fine-grained features (Elgendy, 2020).

Moreover, its use of large filter sizes in early layers and fewer total layers reduces its ability to capture fine details required for tasks like distinguishing between visually similar car models.

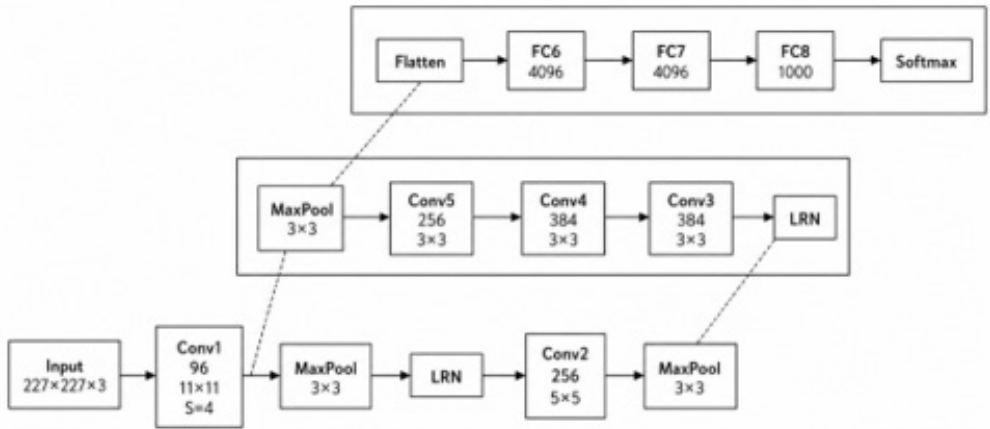


Fig. 3. Used reconstructed AlexNet model summary in this study.

AlexNet demonstrated effective clothing classification, achieving a 74 % accuracy on clean images and 68.28% accuracy on a combined dataset of clean and loss images, showcasing its ability to classify various clothing types using deep learning (Noh, 2021). AlexNet, a deep learning model, is highly efficient in facial expression recognition (FER) due to its computational speed, providing faster results in comparison to other models. It performs well in real-time applications, offering a balance between accuracy and time consumption, making it suitable for dynamic environments such as human- computer interaction and healthcare (Paulchamy et al., 2025). In the comparison of different deep learning models for 3D image segmentation, 3D AlexNet demonstrated superior performance, with higher accuracy and faster training times compared to models like ResNet50 and Inception-V4. Its optimized architecture, including reduced layers and channels, resulted in a classification performance with an AUC value of 0.964, outperforming the other models in terms of accuracy, sensitivity, specificity, and F1-score (Chen et al., 2021). For instance, the modified AlexNet architecture has shown to be a strong and efficient CNN model for the early identification of crop diseases (Chen et al., 2022). It attained an accuracy of 81.07 %, a precision of 82.70 %, and a recall of 80.24 %, indicating competitive effectiveness among similar models (Nugraha et al., 2023). AlexNet, when applied to the CEW dataset for eye state recognition, achieved an accuracy of 97.11% and an AUC of 99.42 %, demonstrating competitive performance. Although it did not outperform the proposed DCNN in terms of both accuracy and AUC, it remains a strong alternative for eye state detection in real-world applications (Kayadibi et al., 2022). Based on the results, the proposed 3D AlexNet achieved competitive performance in brain tumor classification, surpassing existing methods in precision for LGG, HGG, and healthy subjects, though slightly underperforming in overall accuracy compared to a deep CNN approach (Rani, et al., 2022). Based on the results, AlexNet demonstrated superior recognition accuracy (87.8 %) and faster detection performance compared to VGG16 and ResNet18, making it a suitable choice for real-time traffic signal recognition, especially when combined with YOLOv5s and

low-light enhancement techniques (Niu et al., 2022). Based on the results, introducing deconvolution layers into AlexNet significantly reduces model parameters, especially in the fully connected layers, and improves test accuracy by 1–3%, making the enhanced AlexNet both more efficient and more accurate for small-scale image classification (Li et al., 2021). The improved AlexNet model, modified for tomato leaf disease recognition using transfer learning, achieved superior performance with 98.72 % accuracy by fine-tuning layers, adjusting the output to 8 classes, and employing weighted fusion of HOG and LBP features. Compared to traditional models like VGG and SVM based methods, it demonstrated faster convergence, higher recognition accuracy, and stronger generalization (Qiu et al., 2024).

Vehicle Make and Model Recognition (VMMR) refers to the task of identifying a vehicle's make (manufacturer) and model (specific product) from an image or video input. This process is essential for applications in Intelligent Transportation Systems (ITS), where it is used for tasks like traffic management, surveillance, behavior analysis, and monitoring. VMMR helps in automatic vehicle detection at toll stations, real-time traffic condition analysis, and locating stolen vehicles (Lyu et al., 2022). The proposed solution is deeply embedded in the Internet of Things (IoT) ecosystem, linking physical vehicle tags with cloud-based data systems for seamless identification and monitoring (Mufti et al., 2023). Driving style (DS) can be classified as either short term – based on situational behavior or long term – reflecting consistent driving patterns over time; classification methods include both continuous indices for precision and discrete categories for simplicity, influenced by driver, vehicle, and environmental factors (Mei et al., 2025). A hierarchical cloud platform architecture for intelligent vehicle systems, organized into four key layers application, network, platform, and terminal. The terminal layer handles data collection from vehicles and sensors. The network layer ensures communication between vehicles and the cloud. The platform layer is central to the system, offering powerful computing and storage for processing large-scale vehicle data. At the top, the application layer supports services such as driving style recognition, vehicle coordination, and speed planning–leveraging the data processed in the lower layers to deliver intelligent transportation solutions (Mei et al., 2023) (Figure 3).

This study concludes that the proposed TCN-ATM model significantly outperforms traditional models like LSTM, SVM, and TCN in recognizing lane change intentions, while multi-task learning approaches, especially MTL-LSTM, enhance prediction accuracy by leveraging correlations between driving indicators, offering promising applications for improving autonomous vehicle perception and control (Yuan et al., 2023). The reviewed literature provides a detailed overview of energy management strategies (EMSs) for hybrid electric vehicles and driving cycles (DCs) (Liu et al., 2020). This aspect affects road traffic in terms of electric vehicles.

The article (Li et al., 2023) reviews an integrated control strategy for mechanical-electrohydraulic hybrid vehicles (EHHVs) with real-time driving mode recognition. By using PCA for dimensionality reduction, K-means clustering for offline classification, and LVQ neural networks for online mode recognition, the proposed LVQ-fuzzy EMS

improves energy allocation and recovery, optimizing consumption without compromising dynamic performance. The study highlights the potential of EHHVs for efficient power and energy recovery, offering a foundation for future hybrid vehicle EMS and intelligent mode switching.

According to the analysis conducted in the cited study, we developed an algorithm for recognizing and correcting vehicle maneuvers in vibration-based road quality measurement systems. The algorithm demonstrated a 93 % classification accuracy and improved road surface classification by 7 % in suburban areas and 10 % in urban environments, where aggressive maneuvers are more common. By compensating for the impact of these maneuvers, the approach significantly enhanced the accuracy of road quality measurements, offering a scalable and low-cost solution that integrates seamlessly into existing systems (Nagy et al., 2025). This paper introduces an adaptive energy management strategy for hybrid electric tracked vehicles (HETVs), combining deep reinforcement learning (DRL) and transfer learning (TL) to address the challenges of long training times. The proposed bi-level control framework optimizes energy management by integrating DDPG and TL, with a focus on improving adaptability and performance across different driving cycles. Experimental results demonstrate the effectiveness of the approach, offering significant improvements in training efficiency and energy savings (Guo et al., 2020). This paper proposes a multi-sensor feature fusion classification method for vehicle micro-motor noise recognition, inspired by auditory perception principles. By transforming multi-sensor time-domain signals into Mel spectrograms, the method effectively extracts and optimizes features, achieving a high recognition accuracy of 94.90%. The approach also employs SpecAugment for data augmentation, increasing sample volume and improving model training. Experimental results demonstrate its effectiveness, especially in resisting interference in vehicular environments, with an accuracy of 94.27 % under low signal-to-noise ratio conditions (Zhao et al., 2023).

This paper discusses the development of Automatic License Plate Recognition (ALPR) systems, which are widely used in intelligent transportation systems for tasks such as traffic law enforcement, toll collection, and security monitoring. It highlights the transition from traditional methods to deep learning-based approaches, which offer superior accuracy and speed for both license plate detection and recognition. The paper also emphasizes the need for large, diverse datasets to train these models, and it introduces the challenge of character wise annotation for European license plates, which the study aims to address. Furthermore, the work describes a bimodal re-identification system that employs YOLOv5 for detecting vehicles and license plates (Ramajo-Ballester et al., 2024). This paper introduces a GPS trajectory-based machine learning method to better understand vehicle mobility patterns by capturing both travel actions and intentions. It uses DBSCAN clustering to identify high-frequency access locations and a graph-based PCA method to infer the intended destinations of vehicles. The study, based on data from 11,590 vehicles in Beijing, demonstrates that the method can reveal drivers' travel intentions beyond their actual parking locations. The findings show significant

differences between intended destinations and parking behaviors, with drivers heading home more likely to park near residential areas, while those heading to work are less likely to park near office buildings. The method also identifies commuters and non-commuters by analyzing frequent access points, revealing that commuters tend to travel shorter distances compared to non-commuters (Su et al., 2025). VMMR has recently attracted growing interest in AI and computer vision. However, issues like low lighting, bad weather, occlusion, and angle variation still hinder detection accuracy (Berwo et al., 2023).

A standard convolutional network, such as ResNet, can be progressively modernized toward the hierarchical architecture of vision Transformers like Swin, while excluding any attention-based modules. Model accuracies within the ResNet-50 / Swin-T computational regime are represented by the foreground bars, whereas results in the ResNet-200 / Swin-B regime are shown in gray. Hatched bars indicate architectural modifications that were not applied. Detailed quantitative results for both regimes are provided in the appendix.

Incorporation of Transformer-inspired architectural components, such as patchified convolutional stages, normalization refinements, and depth scaling, consistently improves performance. Through these cumulative enhancements, the resulting architecture, known as ConvNeXt, emerges as a purely convolutional model that matches or exceeds the accuracy of the Swin Transformer while maintaining comparable computational efficiency (Liu et al., 2022).

SimCLR, or Simple Framework for Contrastive Learning of Visual Representations, is a self-supervised learning method designed to learn image representations without using labeled data. It operates by maximizing the agreement between two differently augmented views of the same image while minimizing the similarity between views of different images. The approach relies on strong data augmentation techniques—such as random cropping, color distortion, and Gaussian blur—to create correlated image pairs used for training.

A convolutional neural network, typically a ResNet, serves as the base encoder to extract feature representations, which are then mapped to a latent space through a small projection head composed of a multilayer perceptron. In this latent space, the contrastive loss, known as the normalized temperature-scaled cross-entropy (NT-Xent) loss, is applied. This objective encourages high cosine similarity between positive pairs and low similarity between negatives drawn from the same mini-batch.

Through this contrastive framework, SimCLR effectively learns robust and transferable visual representations. It achieves 76.5 % top-1 accuracy on ImageNet under the linear evaluation protocol, surpassing previous self-supervised approaches and establishing a new state of the art in self- and semi-supervised learning (Chen et al., 2020).

CLIP is a language and image based pretraining model that represents and compares visual and textual embeddings. The model jointly encodes textual and visual embeddings on large data sets, optimizing the classification process using cosine

similarity between vectors.

This neural network differs from computer vision models in that it processes natural language, enabling it to generalize to a wide range of visual concepts without explicitly training it on a specific task. During inference, the text encoder can transform class names or descriptions into embeddings, forming a zero-shot linear classifier that allows the model to recognize new categories directly from text.

Through this contrastive training paradigm, CLIP acquires highly transferable and robust representations. It demonstrates strong performance across diverse tasks, including object recognition, OCR, action understanding, and geo-localization, while surpassing supervised ImageNet models in both efficiency and zero-shot generalization capability (Radford et al., 2021).

Two-step detectors (e.g., R-CNN, Fast R-CNN, Faster R-CNN, R-FCN) generally offer higher accuracy but are computationally heavier. One-step detectors (e.g., SSD, YOLO variants, RetinaNet) are faster and better suited for real-time use (Berwo et al., 2023). This paper introduces an enhanced activation function combining ReLU and sigmoid, which shows a significant improvement in recognition accuracy – 8.58 % higher than ReLU and 16.55 % better than LReLU, when tested on the University of Berkeley’s road scene dataset. The model also outperforms sigmoid and Tanh functions on large road datasets, addressing the oscillation issues of LReLU and the inability of ReLU to handle the negative half-axis effectively. While the model still has room for improvement in certain categories, future work will focus on expanding the dataset and optimizing network parameters to boost accuracy. The paper highlights that deep learning models, closely linked to traditional computer vision systems, are improving rapidly in structure, design, and training, with significant advancements expected in the coming years (Li et al., 2023). This paper (Liu et al., 2024) introduces a view-independent vehicle model recognition framework using object detection and image retrieval techniques, designed for edge-cloud systems. Tested on the Stanford Cars dataset, the approach outperforms most previous methods in terms of accuracy and efficiency. The image screening and component detection processes reduce search time and calculation costs, making the model more efficient. Unlike traditional end-to-end methods, this two-stage approach avoids repeated training when the sample set changes, offering adaptability for large-scale and multi-category vehicle recognition. The results suggest strong potential for real-time applications, with future work focusing on improving feature descriptors and developing an adaptive vehicle model recognition system (Liu et al., 2024). ViTs have gained attention for their strong performance in image tasks, thanks to the MSA module that models global interactions. However, their generalization can be limited due to a lack of inductive bias for local relations. To overcome this, CNN-Transformers (HVTs) combine self-attention and convolution, enhancing performance by learning both local and global features. Various methods, like early and parallel integration, have been proposed to incorporate convolutional bias into transformers. Despite challenges, HVTs show great potential for real-world computer vision applications (Khan et al., 2023).

Convolutional Neural Networks (CNNs) have become a popular choice for

Acoustic Target Recognition (ATR) in acoustic images, offering superior performance over traditional template-matching techniques. Unlike template matching, which struggles with generalizing patterns and handling multi-scale objects, CNNs are capable of learning relevant features directly from the data. The hierarchical structure of the CNN allows for the extraction of simple edge features and complex patterns in deep layers. This is suitable for ATR tasks such as object detection and classification in acoustic images. In the paper, the models demonstrated their effectiveness even with computational limitations and in an underwater environment (Bresciani et al., 2024). The reviewed study discusses the issues of hyperparameter tuning for deep reinforcement learning (DRL), in particular the impact of network capacity on performance (Palomeras et al., 2024).

This study focuses on the detection and recognition of vehicles and their license plates using deep learning methods, specifically leveraging pre-trained YOLO models for vehicle detection. The task involves identifying regions of interest (ROIs) within images that correspond to vehicles and license plates. The work also highlights the importance of large, diverse datasets for training vehicle recognition models, with several datasets mentioned, such as Stanford-Cars, VehicleID, and VeRi-776, which contain extensive image collections with varying levels of camera coverage and annotations. These datasets are critical for improving the performance of vehicle re-identification systems, ensuring the models can handle different vehicle types, camera angles, and environmental conditions (Ramajo-Ballester et al., 2024). The study under review examines the use of long-short-term memory (LSTM) models for recognizing vehicle engine dynamics. Instead of k-means methods, the paper uses an autoencoder for data dimensionality reduction and spectral clustering. Nonlinear dimensionality reduction improves the model's robustness to noisy data (Chen et al., 2024). The TSDR-KNN model was created for character recognition in clear images. It processes inputs through a convolutional layer to extract relevant features and applies a max-pooling operation to enhance its efficiency. On the other hand, HRU-Net focuses on image recovery by combining a compact CNN with a self-adaptive image processing (SAIP) module for enhanced image clarity post-defogging. This approach incorporates filters for white balance, contrast, gamma correction, and sharpening, optimizing the image by reducing chromatic aberration and restoring lost details in darker regions (Rani et al., 2024). This study compares five driving condition recognition methods, highlighting the navigation-based method's high accuracy in most driving cycles, though it struggles with blended conditions like WLTP. Clustering showed the best fuel economy improvement, while fuzzy logic had the lowest. The study recommends using the navigation based method in the vehicle concept phase and clustering in production. Future research may focus on hardware testing and the impact of autonomous driving technologies (Xu et al., 2023). The proposed representative sample selection method significantly improves recognition rates compared to random and regular methods, offering a foundation for targeting and obtaining samples that optimize recognition algorithm performance in limited conditions (Zhang et al., 2024). This article explores different motion segmentation

and appearance-based methods used for vehicle recognition. The text emphasizes the importance of these techniques in applications like traffic surveillance, urban planning, and security (Kanagamalliga et al., 2024).

MobileNet is built on depthwise separable convolutions, a form of factorized convolution that divides a standard convolution into two stages: a depthwise convolution and a pointwise convolution. In this structure, the depthwise convolution applies a single filter to each input channel independently, while the pointwise convolution, implemented as a 1×1 convolution, combines the resulting feature maps across channels. This separation of spatial filtering and channel mixing drastically reduces computational cost and model size compared to conventional convolutions (Khasoggi et al., 2019). MobileNets are lightweight convolutional neural networks designed to minimize computational latency while maintaining accuracy. They achieve this efficiency through depthwise separable convolutions, which separate spatial and channel operations to reduce parameters and operations. This architecture enables fast inference on resource-limited devices such as mobile and embedded systems (Howard et al., 2017). Thus, it is a more advanced neural network that optimizes and creates new features to classify using adaptive depthwise and pointwise convolutions. The mobile network structure used in the study is also shown in Figure 4.

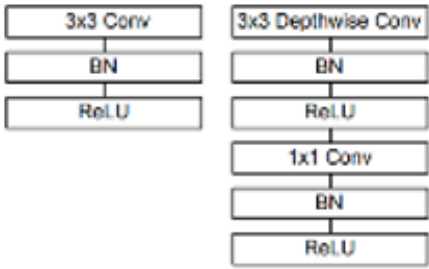


Fig. 4. “Left: Standard convolutional layer with batchnorm and ReLU. Right: Depthwise Separable convolutions with Depthwise and Pointwise layers followed by batchnorm and ReLU.” (Howard et al., 2017; p. 4).

EfficientNet is a convolutional neural network architecture designed to optimize both accuracy and computational efficiency through compound scaling of network depth, width, and resolution. It achieves high performance with fewer parameters by uniformly scaling these dimensions using a simple, principled method (Pu et al., 2024). EfficientNet is a family of convolutional neural networks developed through neural architecture search and compound scaling, which jointly optimizes network depth, width, and resolution. This design achieves a balance between accuracy and efficiency, outperforming previous convolutional models in both performance and computational cost. EfficientNet architectures also generalize well across diverse datasets, demonstrating strong transfer learning capabilities with compact model sizes (Tan et al., 2020). EfficientNet scales, allocates resources, and adapts to feature classification using 5 scaling methods.

The Vision Transformer (ViT) is a deep learning architecture that applies the Transformer model to image analysis by dividing images into patches and processing

them as sequences using self-attention mechanisms. This approach enables ViT to effectively capture spatial relationships within images without relying on traditional convolutional operations (Zhang et al., 2023). The ViT-B/16 model demonstrates high effectiveness in automated medical image analysis, achieving near-perfect accuracy in identifying elbow fractures from X-ray images, thereby significantly improving the reliability of diagnostic systems (Alam et al., 2024). The Vision Transformer (ViT) uses only the encoder of the Transformer architecture. It divides an image into fixed-size patches, projects each patch into a vector, and processes them as a sequence. A special classification token is added to the sequence, and its output represents the final class prediction (Huo et al., 2023). Visual transformers are closely related to the theory of text transformers and encoders, they use these methods and divide the main image into a sequence of embeddings.

Table 1. Comparison of Strengths and Weaknesses of CNN Models

Model	Strengths	Weaknesses
ResNet50	Mitigates vanishing gradients; enables deep training; fast convergence; good on small datasets; customizable for tasks	High computational cost; struggles with unusual distributions; overfitting without regularization; adversarial vulnerability; redundant features in deep layers
VGG19	Simple, uniform architecture; strong feature extraction with small filters; high accuracy; stable training	Very large parameter count; overfits small datasets; lacks skip connections; inefficient gradient flow
AlexNet	Pioneering deep learning model; includes dropout, ReLU, and overlapping pooling; efficient early training	Shallow depth; underfits high-res data; lacks fine feature extraction; not suited for fine-grained recognition
MobileNet	Uses fewer resources, more chances for feature recognition due to architecture.	Performance drops on large-scale or complex datasets due to limited representational capacity.
	Focus on scaling to achieve the desired accuracy and classification features	Compound scaling is computationally expensive to design and retrain for new domains.
ViT	Improved efficiency in object detection. An approach different from the CNN in defining objects	Requires large-scale datasets for effective training due to the absence of inductive biases like locality and translation invariance.
ConvNeXt	Increased convolution layers to 7x7 for better accuracy, increased kernel size. Fewer activation functions. Replacing ReLU with GELU. Fewer normalization layers	High attention cost. Needs more resources to input.
SimCLP	A simple and effective self-supervised framework that learns powerful visual representations without labels.	It achieves high accuracy but requires large batch sizes and extensive computational resources.
CLIP	A multimodal model that aligns images and text in a shared embedding space, enabling strong zero-shot generalization.	Its broad versatility comes at the cost of reliance on massive pretraining data and potential bias from web-scale text sources. Lack of text embeddings for models.

This work is a continuation of the development of the VM MR application for analyzing vehicle traffic.

Literature analysis of existing systems. Finding the values of car models that affect city traffic, searching for these values of certain brands in official vehicle documentation.

Training existing models to classify car brands and detect cars, determine their type.

In this article, the models described above were trained under identical conditions and analyzed using metrics, LIME, SHAP, and GradCam analyzers. The output data will help compare the performance of the models in identifying a car model from an image.

An existing dataset of car models was used for classification training, which contains 291,752 images of cars of the brand from 1950 to 2016 (Tafazzoli et al., 2017). This dataset is publicly available. Most vehicle classes refer to the year 2015 when the image was made. Most of the samples in the dataset are rendered in 3D free (complex angles). After filtering and dividing the dataset into the training and testing ones, 283,899 images and 7,982 classes of car models (1,188 skipped classes) remained. A cloud resource with an NVIDIA RTX 4000 Ada Generation GPU was used. The images were transformed to a size of 256x256 and randomly resized and cropped to 224x224. Some images were horizontally mirrored. Color Jitter was used to improve robustness, converting some images to grayscale $p=0.03$. Standardizes pixel values using ImageNet normalization parameters $\text{mean} = [0.485, 0.456, 0.406]$, $\text{std} = [0.229, 0.224, 0.225]$. Preprocessing also used horizontal flipping and zooming methods. The models used the Adam optimizer. All models were trained under the same environment and conditions: epochs = 10, batch size = 32.

Jupiter notebook, saved models and other resources of this study are available in cloud storage (Mordvintsev, 2025).

Results and discussion.

Identifying the factors related to car models that influence city traffic and investigating these factors for specific brands through official vehicle documentation.

The size of a vehicle affects its maneuverability and the space it occupies on the road. Large vehicles require more room to maneuver, which reduces traffic speed and increases congestion. Turning radius also plays a significant role, affecting maneuver times at intersections.

The analyzed modern approaches to data processing, and the focus on vehicle identification and subsequent interpretation of characteristics.

Re-identification is the process of matching the appearance of objects within and between camera networks. Typically, this involves a user searching for all occurrences of a queried object across the cameras in a network. For example, a traffic officer may be trying to locate a specific car in the city camera system. Using of a deep CNN learning model to identify same car model images (Elgendy, 2020).

The classification of different machine learning approaches is based on the varying angles of the datasets utilized in these studies. The main objective of this analysis is to provide an overview of the current achievements of the VMMR and to highlight potential areas for development. This classification includes frontal, rear, multiview and miscellaneous perspectives (Elgendy, 2020). Current research working with frontal and back side car views.

A deep CNN ResNet50 was used as the backbone network to extract object-level features. In another approach, a hybrid approach combining the deep VGG16 model

with a Genetic Algorithm (GA) was proposed. In addition, a new loss function was introduced to improve the performance of deep CNN models (Elgendy, 2020).

There are three main learning techniques for training a model: supervised, unsupervised, and reinforcement learning. Hyperparameter tuning is also crucial to improve the performance of a model. Transfer learning uses pre-trained models to improve task performance. The model adaptation process uses model coefficients and trains on a large dataset specific to the task.

Data transformation methods transform images to focus on identifying patterns and features. This implementation included horizontal flipping, random rotation, and image normalization.

Accuracy and loss metrics of models.

The evaluation metrics of the trained models are presented in Figures 5–13.

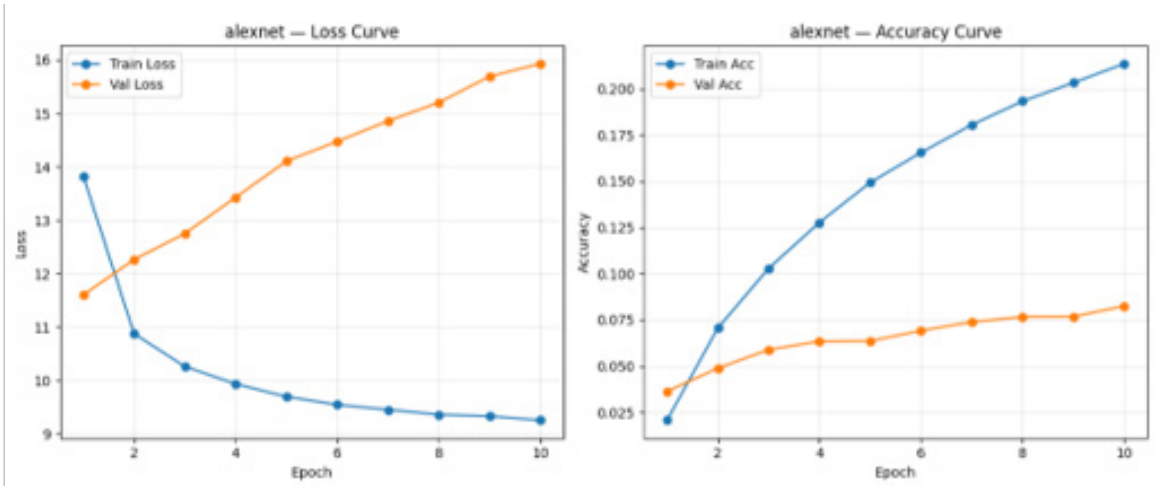


Fig. 5. AlexNet accuracy/loss.

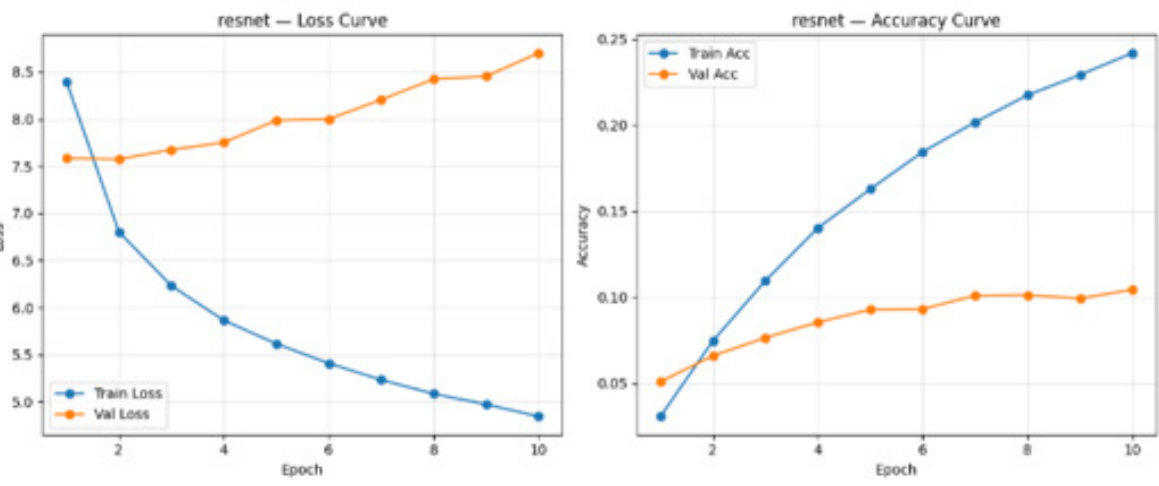


Fig. 6. ResNet accuracy/loss.

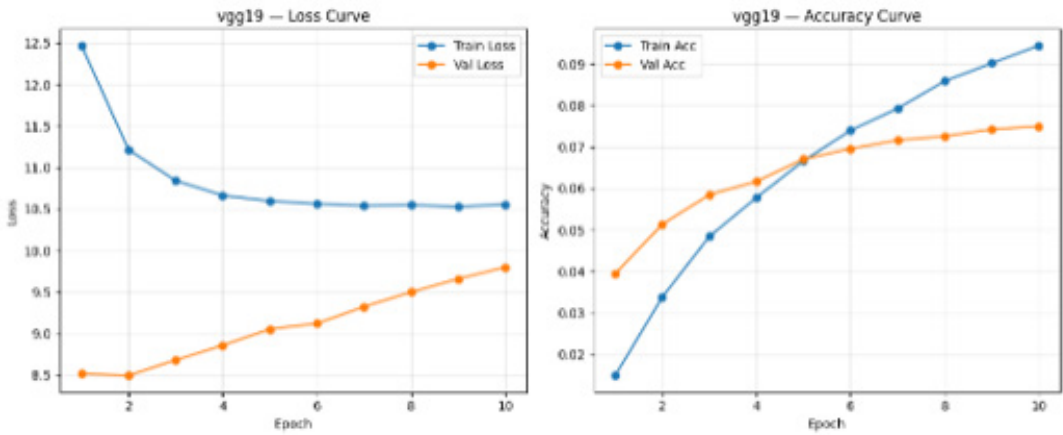


Fig. 7. VGG19 accuracy/loss.

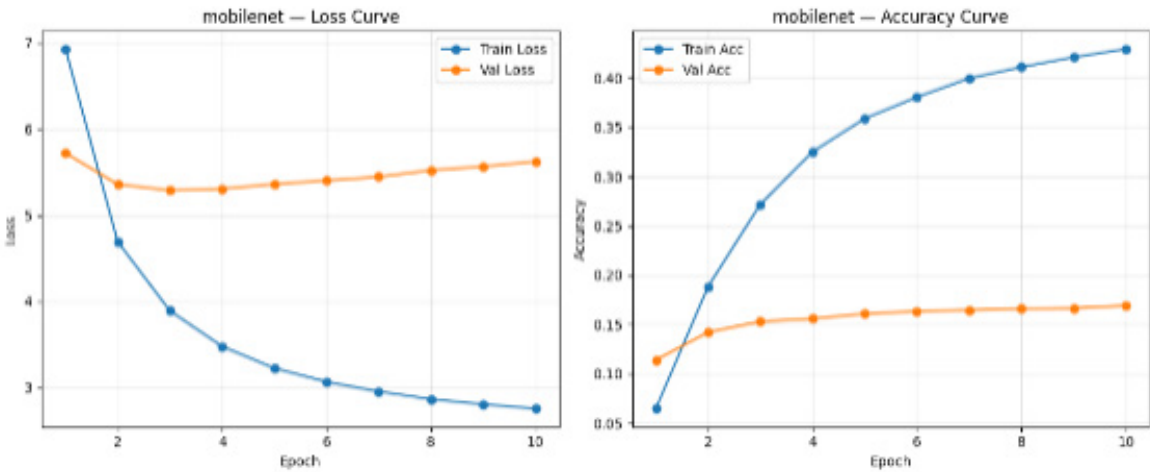


Fig. 8. MobileNet accuracy/loss.

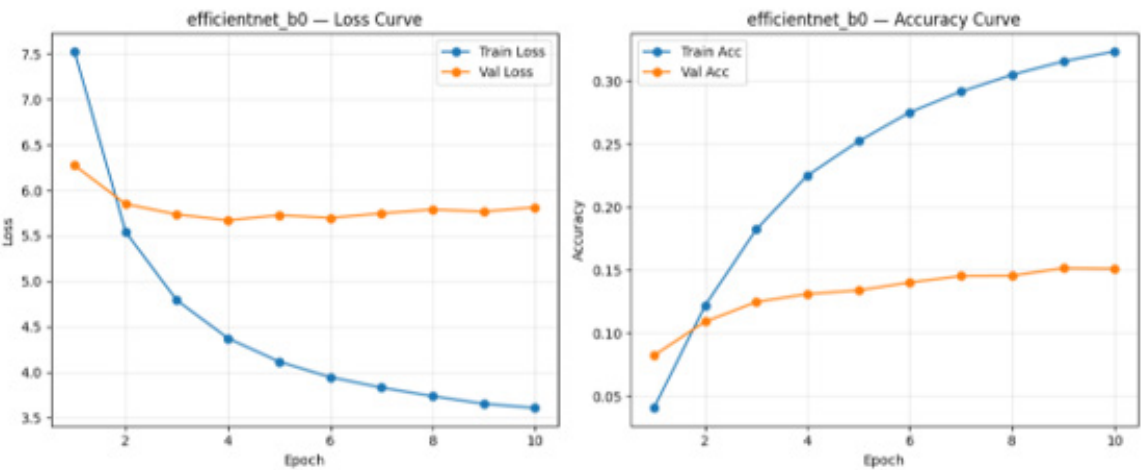


Fig. 9. EfficientNet accuracy/loss.

For the current training, the EfficientNet layers were scaled in depth and finally in breadth for classification.

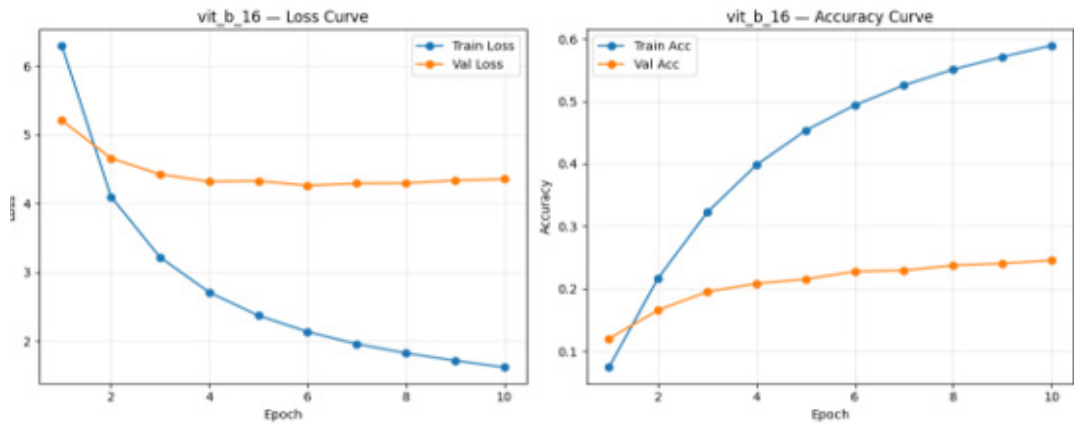


Fig. 10. ViT b16 accuracy/loss.

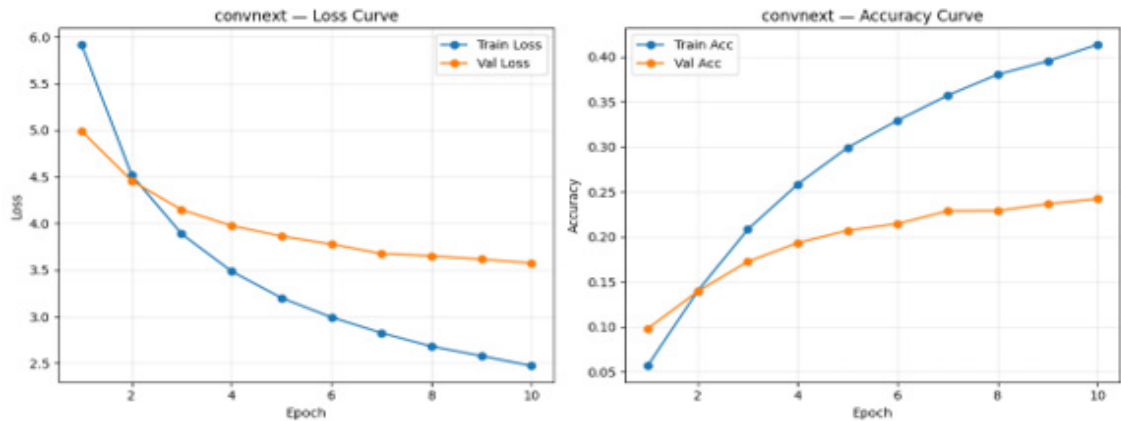


Fig. 11. ConvNeXT accuracy/loss.

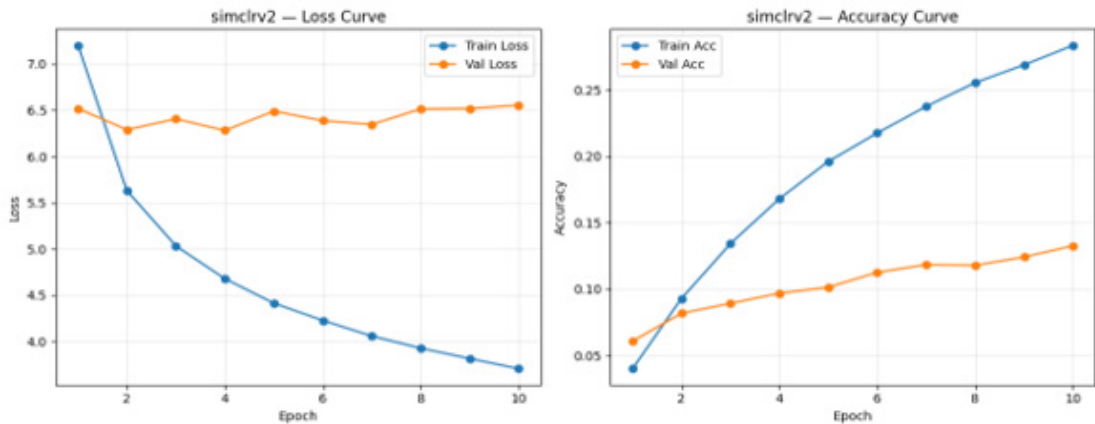


Fig. 12. SimCLRv2 accuracy/loss.



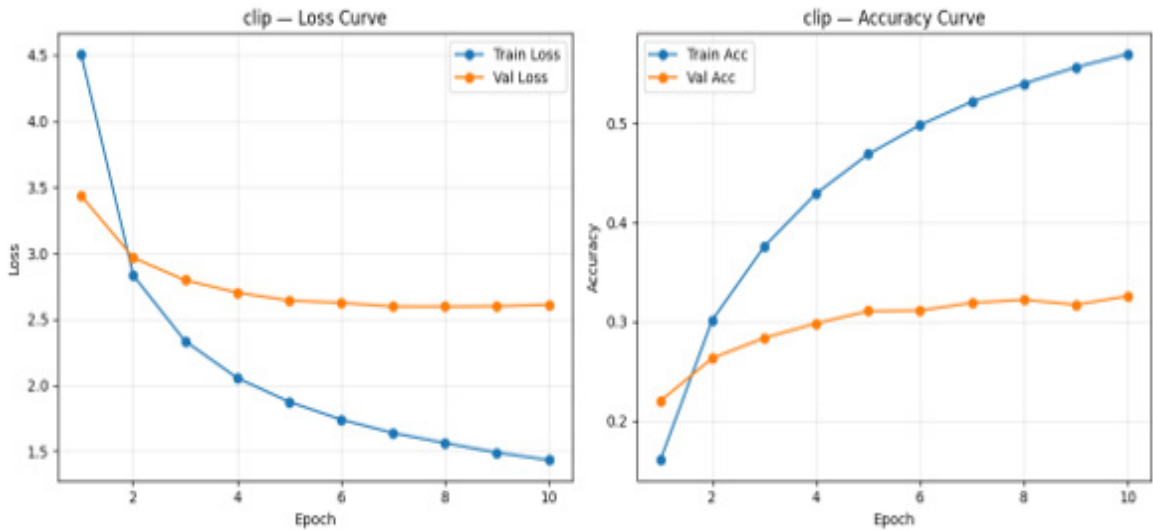


Fig. 13. CLIP accuracy/loss.

The comparison of model accuracy and loss is presented in Table 2.

Table 2. Comparison of Accuracy and Loss of models from Figures 5-13.

Model	Final train loss	Final validation loss	Final train accuracy	Final validation accuracy
AlexNet	9.2563	15.9313	21.36 %	8.26 %
ResNet	4.8434	8.7011	24.19 %	10.44 %
VGG19	10.5568	9.8006	9.44 %	7.49 %
MobileNet	2.7533	5.6254	42.95 %	16.91 %
EfficientNet	3.6078	5.8118	32.36 %	15.09 %
ViT b16	1.6194	4.3545	58.95 %	24.55 %
ConvNeXt	2.4711	3.5753	41.34 %	24.21 %
SimCLR	3.7059	6.5539	28.35 %	13.27 %
CLIP	1.4322	2.6097	56.98 %	%

As can be seen in Table 2, scalable networks have an advantage in classifying machine models, especially ConvNeXt, ViT b16 and CLIP.

Locally Interpretable Model-Agnostic Explanations analysis

From the visualization of 32 main features, it can be seen that the EfficientNet contains more accurate 2 negative features, while the negative features of the others are all over the picture Table 3. From the properties of convolutional networks, it can be seen that all models distinguish between the boundaries of the machine and the environment. All models except AlexNet mark the components of the car. As you can see, trained CLIP highlights complex areas grouped together and has greater semantic analysis.

Gradient weighted Class activation mapping analysis.

Table 3 presents Locally Interpretable Model-Agnostic Explanations (LIME) analysis of models.

Table 3. LIME analysis of models.

Model	Correct Top-k First	Top-1 accuracy	Positive features on car shape	Negative features on car shape	Mean absolute difference
AlexNet	No	0.996	11	1	0.7966
ResNet	No	0.168	12	1	0.0580
VGG19	No	0.080	10	1	0.0096
MobileNet	Yes	0.857	14	1	0.6702
EfficientNet	Yes	0.567	12	2	0.4127
ViT b16	Yes	0.331	11	1	0.1880
ConvNeXt	No	0.074	9	1	0.0159
SimCLR	Yes	0.663	11	1	0.4939
CLIP	Yes	0.990	5 (2 complex)	1	0.7908

Figures 14–22 show the results of gradient weighted class activation mapping.

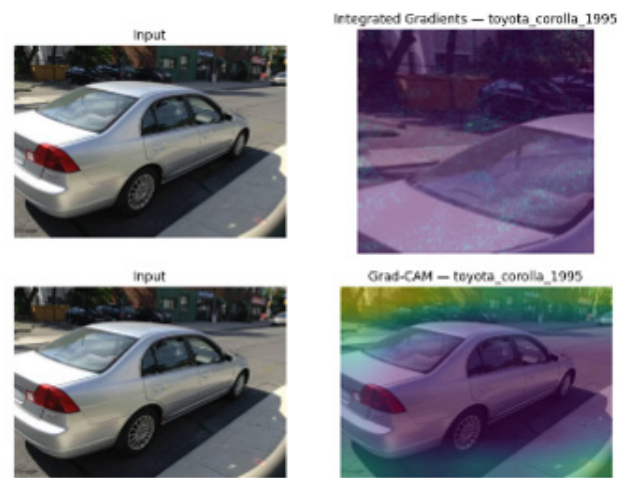


Fig. 14. AlexNet GradCam.



Fig. 15. ResNet GradCam.



Fig. 16. VGG19 GradCam.



Fig. 17. MobileNet GradCam.



Fig. 18. EfficientNet GradCam.



Fig. 19. ViT b16 GradCam.



Fig. 20. ConvNeXt GradCam.



Fig. 21. SimCLR GradCam.



Fig. 22. CLIP GradCam.

The scaled models have a larger gradient on the machine, while in Figures 14-19 they are noisier. Also the gradient being divided into squares in the visual transformer

and CLIP Figures 19 and 22. SHapley Additive exPlanations analysis

Table 4 presents SHAP analysis of models.

Table 4. SHAP analysis of models

Model	Correct Top-k First	Top-1 accuracy	Mean absolute difference
AlexNet	No	0.2	0.048
ResNet	No	0.2	0.048
VGG19	No	0.1	0.000
MobileNet	Yes	0.9	0.716
EfficientNet	Yes	0.6	0.422
ViT b16	Yes	0.4	0.238
ConvNeXt	No	0.1	0.022
SimCLR	Yes	0.65	0.476
CLIP	Yes	0.99	0.791

Although the visual transformer has greater accuracy, MobileNet, SimCLR and EfficientNet shows a contrast in classification (average absolute difference between top k) Table 4. Also, the MobileNet does not show attribution in the center of the hit map, unlike other models.

Discussion.

This work opens up new possibilities for the implementation of road analysis in a smart city. The semantic capabilities of current deep learning networks for determining complex information about a car brand model were considered. New possibilities for dynamic analysis of cars on the road open up a new look at formulas for calculating traffic lights and other road regulations. This research also observes unpredictable different behavior of similar deep learning models on the same dataset. The results show that scalable networks have potential for semantic recognition, and it is also noted that image tokenization also shows high performance in identifying different models of similar objects (cars).

The validation accuracy is below 30 %, which may indicate accuracy on new images in production mode. The evaluation was based on static test sets; model robustness under varying conditions (motion blur, night lighting, etc.) remains untested. Production mode of training requires multi-view dataset for recognition. Some highlighted LIME or SHAP regions may not correspond to true discriminative car features (e.g., background influence in first 32 features).

Creating simulations of rain, night, blur, and seasons using images from the dataset. Supplementing the dataset with other points of view on the machine. Increasing learning epochs.

Conclusion.

In this article, certain factors were found that are related to both the car model and the user experience of the road and the infrastructure of smart city roads. It was also found that not all factors are recorded in the documentation of the models with a direct value, for example, the size of the rotation of the car. Various modern approaches to

classifying a car model by a two-dimensional image were analyzed. Scalable and non-scalable models were compared.

This study reviewed current data processing and analysis methods for vehicle detection and classification based on deep learning architectures. ResNet50, VGG19, AlexNet, MobileNet, EfficientNet, Vision Transformer (ViT-B16), ConvNeXt, SimCLR, and CLIP models have been trained and tested on a massive dataset comprised of 283,899 vehicle images.

The experimental results showed that all the models succeeded in learning a rough appearance-based model of vehicles with a validation accuracy range of 0.07-0.32, revealing that there remain significant issues regarding dataset complexity, inter-class similarity, and possible imbalance of the data distribution. Classical convolutional architectures like VGG19 and ResNet50 were average performers, while more recent architectures like ConvNeXt and ViT-B16 have superior feature extraction capabilities, but they are increasingly demanding in terms of fine-tuning and computational power. Self-supervised and contrastive methods (SimCLR and CLIP) emphasized that transfer learning from large pre-trained representations is promising, but they are no match for domain-specific adaptations.

In conclusion, the study confirms that deep learning is still a promising approach for vehicle recognition but it is still far from trivial to obtain high accuracy with them without performing proper data pre-processing, class balancing, and model tuning. The results highlight the relevance of domain adaptation, augmentation techniques, and architecture dependent tuning for improving generalization. Future works may investigate hybrid or ensemble methods, transformer CNN based architectures, contrastive pretraining on domain related vehicle datasets for further enhancements in the reliability of detection and identification for practical real-life ITSs.

REFERENCES

- Awan M.J., Masood O.A., Mohammed M.A., Yasin A., Zain A.M., Damas˘evic˘ius R. and Abdulkareem K.H. (2021). Image-based malware classification using VGG19 network and spatial convolutional attention // *Electronics*. — Vol. 10. — No. 19.
- Alam, Taukir & Yeh, Wei-Cheng & Hsu, Fang & Shia, Wei-Chung & Robert Singh, A. & Hassan, Taimoor & Lin, Wenru & Yang, Hong-Ye & Hussain, Tahir (2024). An Integrated Approach using YOLOv8 and ResNet, SeResNet & Vision Transformer (ViT) Algorithms based on ROI Fracture Prediction in X-ray Images of the Elbow. *Current medical imaging*. 20. 10.2174/0115734056309890240912054616.
- Berwo M.A., Khan A., Fang Y., Fahim H., Javaid S., Mahmood J., Abideen Z.U. and MS S. (2023). Deep learning techniques for vehicle detection and classification from images/videos: A survey // *Sensors*. — Vol. 23. — No. 10. Pp. 4832.
- Bresciani M., Zacchini L., Topini A., Ridolfi A., and Costanzi R. (2024). Automatic target recognition and geolocalisation of natural gas seeps using an autonomous underwater vehicle. *Control Engineering Practice*. — Vol. 145. — P. 105864.
- Chen, T., Kornblith, S., Norouzi, M., & Hinton, G. (2020, November). A simple framework for contrastive learning of visual representations. In *International conference on machine learning*. Pp. 1597-1607. PmLR.
- Chen J., Wan Z., Zhang J., Li W., Chen Y., Li Y., and Duan Y. (2021). Medical image segmentation and reconstruction of prostate tumor based on 3d alexnet // *Computer methods and programs in biomedicine*. — Vol. 200. — P. 105878.
- Chen H.-C., Widodo A.M., Wisnujati A., Rahaman M., Lin J.C.-W., Chen L., and Weng C.-E. (2022). Alexnet convolutional neural network for disease detection and classification of tomato leaf // *Electronics*. — Vol. 11. — No. 6. P. 951.

- Chowdhury M.T., Rahman H., Sumon M.I., and Talha A. (2024). Classification of satellite images with vgg19 and convolutional neural network (CNN), in 2024 2nd International Conference on Advancement in Computation Computer Technologies (InCACCT). Pp. 397–402.
- Chen Y., Yang C., Wang W., and Gao P. (2024). Energy management for hybrid electric vehicles using an intelligent recognition method of engine characteristics. *IFAC-PapersOnLine*. — Vol. 58. — No. 29. Pp. 379–384.
- Hoang T.N. and Kim D. (2024). Supervised contrastive resnet and transfer learning for the in-vehicle intrusion detection system. *Expert Systems with Applications*. — Vol. 238. — Article 122181.
- Hongwen Pu. & Keyi Yi. (2024). A Comparative Analysis of EfficientNet and MobileNet Models' Performance on Limited Datasets: An Example of American Sign Language Alphabet Detection. *Highlights in Science, Engineering and Technology*. No. 94. Pp. 558–564. 10.54097/yh5d3s04.
- Han B., Du J., Jia Y., and Zhu H. (2021). Zero-watermarking algorithm for medical image based on VGG19 deep convolution neural network // *Journal of Healthcare Engineering*. — Vol. 2021. — No. 1. P. 5551520.
- Howard A.G., Zhu M., Chen B., Kalenichenko D., Wang W., Weyand T., Andreetto M., and Adam H. (2017). MobileNets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*.
- Huo, Yingzi & Jin, Kai & Cai, Jiahong & Xiong, Huixuan & Pang, Jiacheng. (2023). Vision Transformer (ViT)-based Applications in Image Classification. Pp. 135–140. 10.1109/BigDataSecurity-HPSC-IDS58521.2023.00033.
- Ikechukwu A.V., Murali S., Deepu R., and Shivamurthy R. (2021). Resnet-50 vs VGG-19 vs training from scratch: A comparative analysis of the segmentation and classification of pneumonia from chest x-ray images // *Global Transitions Proceedings*. — Vol. 2. — No. 2. Pp. 375–381.
- Girhe N., Patel F., Kale P., Mahure A., and Bhute A. (2022). “Smart traffic system to optimize city traffic. *YMER* 21.12. Pp. 972–994.
- Jabeen S., Jabeen A.J., Adnan S.M., and Rao W.A. (2021). Vehicle Make and Model Recognition Using Structural and Pattern Based Feature Descriptors, 2021 // *International Conference on Communication Technologies (ComTech)*. Pp. 73–78. DOI:10.1109/ComTech52583.2021.9616857.
- Jing E., Zhang H., Li Z., Liu Y., Ji Z., and Ganchev I. (2021). ECG heartbeat classification based on an improved ResNet-18 model // *Computational and Mathematical Methods in Medicine* 2021. Article 6649970.
- Khan A., Rauf Z., Sohail A., Khan A.R., Asif H., Asif A. and Farooq U. (2023). A survey of the vision transformers and their CNN-transformer based variants. *Artificial Intelligence Review*. No. 56. Pp. 2917–2970.
- Khan, M.S.M. Ahmed M., Rasel R.Z., and Khan M.M. (2021). Cataract detection using convolutional neural network with VGG-19 model, in 2021 IEEE World AI IoT Congress (AIIoT). Pp. 0209–0212. IEEE.
- Kayadibi I., Guraksin G.E., Ergun U., and Ozmen Suzme N. (2022). An eye state recognition system using transfer learning: Alexnet-based deep convolutional neural network // *International Journal of Computational Intelligence Systems*. — Vol. 15. — No. 1. P. 49.
- Kanagamalliga S., Kovalan P., Kiran K., and Rajalingam S. (2024). Traffic management through cutting-edge vehicle detection, recognition, and tracking innovations // *Procedia Computer Science*. — Vol. 233. — Pp. 793–800.
- Khasoggi, B. & Ermatita, E. & Samsuryadi, S. (2019). Efficient mobilenet architecture as image recognition on mobile and embedded devices // *Indonesian Journal of Electrical Engineering and Computer Science*. — Vol. 16. — No. 389. 10.11591/ijeecs.v16.i1. Pp. 389-394.
- Li S., Wang L., Li J., and Yao Y. (2021). Image classification algorithm based on improved AlexNet // in *Journal of Physics: Conference Series*. — Vol. 1813. P. 012051. IOP Publishing.
- Lyu Y., Schiopu I., Cornelis B., and Munteanu A. (2022). Framework for vehicle make and model recognition—a new large-scale dataset and an efficient two-branch–two-stage deep learning architecture // *Sensors*. — Vol. 22. — P. 8439.
- Liu Z., Mao H., Wu C.Y., Feichtenhofer C., Darrell T. & Xie S. (2022). A convnet for the 2020s., In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. Pp. 11976–11986.
- Li B. and Lima D. (2021). Facial expression recognition via resnet-50 // *International Journal of Cognitive Computing in Engineering*. — Vol. 2. Pp. 57–64.
- Liu C., Pu Z., Li Y., Jiang Y., Wang Y., and Du Y. (2024). Enabling edge computing ability in view-independent vehicle model recognition // *International Journal of Transportation Science and Technology*. No. 14. Pp. 73–86.
- Li S., Wang L., Li J., and Yao Y. (2021). Image classification algorithm based on improved AlexNet // *Journal of Physics: Conference Series*. — Vol. 1813. P. 012051.
- Li L., Zhang T., Lu L., Zhang H., Yang J., and Zhang Z. (2023). An energy active regulation management strategy based on driving mode recognition for electro-hydraulic hybrid vehicles. *Energy*. — Vol. 285. — P. 129548.
- Lin C.-L. and Wu K.-C. (2023). Development of revised Resnet-50 for diabetic retinopathy detection. *BMC*

bioinformatics 24.1. P. 157.

Mascarenhas S. and Agarwal M. (2021). A comparison between VGG16, VGG19 and ResNet50 architecture frameworks for image classification, in 2021 International conference on disruptive technologies for multi-disciplinary research and applications (CENTCON). — Vol. 1. Pp. 96–99. IEEE.

Mohite, Sagar & Jadhav, Swati & Mohite, Snehal & Jagadale-Patil, Devyancee- Netra & Gayakwad, Milind & Singh, Kartikey & Joshi, Rahul. (2025). Vehicle identification using ResNet-50: CNN approach, in 2024 IEEE International Conference on Blockchain and Distributed Systems Security (ICBDS). Pp. 1–6. IEEE.

Meena G., Mohbey K.K., Indian A., and Kumar S. (2022). Sentiment analysis from images using vgg19 based transfer learning approach // *Procedia Computer Science*. — Vol. 204. — Pp. 411–418.

Mufti N., Ullah S., Sharif A., Nawaz M.W., Alkhayyat A., Imran M.A., Abbasi Q.H. (2023). IoT-enabled vehicle recognition system using inkjet-printed windshield tag and 5 G cloud network // *Internet of Things*. — Vol. 23. — Pp. 100873.

Mordvintsev, N. (2025). Jupyter notebooks and resources [Data set]. Astana IT University. <https://drive.google.com/drive/folders/1qmm7Pnmpgxoab7s3fpog4b-3zaawzvzQ?usp=sharing>.

Noh S.K. (2021). “Recycled clothing classification system using intelligent IoT and deep learning with AlexNet // *Computational Intelligence and Neuroscience*. — Vol. 2021. No. 1. P. 5544784.

Nagy R. and Szalai I. (2025). Vehicle maneuver recognition and correction algorithm for road quality measurement system optimization. *Measurement: Sensors*. Article. 101816.

Naaman O. (2022). Resnet and LSTM-based accurate approach for license plate detection and recognition. *Traitement du Signal*. — Vol. 39. — No. 5. Pp. 1577–1583.

Nguyen T.H., Nguyen T.N., and Ngo B.V. (2022). A VGG-19 model with transfer learning and image segmentation for classification of tomato leaf disease. *AgriEngineering*. — Vol. 4. — No. 4. Pp. 871–887.

Niu C. and Li K. (2022). Traffic light detection and recognition method based on YOLOv5s and AlexNet // *Applied Sciences*. — Vol. 12. — No. 21. P. 10808.

Qiu J., Lu X., Wang X., Chen C., Chen Y., and Yang Y. (2024). Research on image recognition of tomato leaf diseases based on improved AlexNet model. *Heliyon*. — Vol. 10. — No. 13.

Praveen S.P., Srinivasu P.N., Shafi J., Wozniak M., and Ijaz M.F. (2022). Resnet-32 and fastai for diagnoses of ductal carcinoma from 2d tissue slides // *Scientific Reports*. — Vol. 12. — No. 1. Pp. 20804.

Palomeras N. and Ridao P. (2024). Autonomous underwater vehicle docking under realistic assumptions using deep reinforcement learning. *Drones*. — Vol. 8. — P. 673.

Ramajo-Ballester A., Moreno J.M.A., and de la Escalera Hueso A. (2024). Dual license plate recognition and visual features encoding for vehicle identification. *Robotics and Autonomous Systems*. — Vol. 172. P. 104608.

Rani A.R., Anusha Y., Cherishama S., and Laxmi S.V. (2024). Traffic sign detection and recognition using deep learning-based approach with haze removal for autonomous vehicle navigation. *e-Prime-Advances in Electrical Engineering, Electronics and Energy*. — Vol. 7. Pp. 100442.

Ronald M., Poulse A., and Han D.S. (2021). Isplinception: an inception-ResNet deep learning architecture for human activity recognition. *IEEE Access* 9. Pp. 68985–69001.

Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S. & Sutskever, I. (2021, July). Learning transferable visual models from natural language supervision. In *International conference on machine learning*. Pp. 8748–8763. PmLR.Sarwinda D., Paradisa R.H., Bustamam A., and Anggia P. (2021). Deep learning in image classification using residual network (Resnet) variants for detection of colorectal cancer // *Procedia Computer Science*. — Vol. 179. Pp. 423–431.

Rani S., Ghai D., Kumar S., Kantipudi M.P., Alharbi A.H., and Ullah M.A. (2022). Efficient 3d alexnet architecture for object recognition using syntactic patterns from medical images // *Computational Intelligence and Neuroscience*. — Vol. 2022. No. 1. P. 7882924.

Sharma V., Kumar V. and Aditya H. (2023). Traffic Sign Detection and Classification, 2023 IEEE International Conference on Computer Vision and Machine Intelligence (CVMI). — Gwalior, India. Pp. 1–6. DOI: 10.1109/CVMI59935.2023.10464876.

Su Z., Liu X., Li H., Zhang T., Liu X., and Jiang Y. (2025). A vehicle trajectory-based parking location recognition and inference method: Considering both travel action and intention. *Sustainable Cities and Society*. — Vol. 119. — P. 106088.

Siva P., Pujitha G.B., Krishna G.S., Hemanth G., and Teja B.M.S. (2025). Computer Vision Enabled Smart Surveillance for Urban Traffic Control // *International Journal on Advanced Computer Engineering and Communication Technology*. — Vol. 14. — No. 1. Pp. 48–55.

Tafazzoli F., Nishiyama K., and Frigui H. (2017). A large and diverse dataset for improved vehicle make and model recognition, in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*

Workshops. Pp. 1–8. <https://github.com/faezetta/VMMRdb>.

Vahora A., and Vahora S. (2025). Optimizing Traffic Flow in Smart Cities with Intelligent Network Management. *FMDb Transactions on Sustainable Intelligent Networks* 2.2. Pp. 91–100. DOI:10.69888/FTSIN.2025.000383.

Yang Z. (2021). Classification of picture art style based on VGGNet // in *Journal of Physics: Conference Series*. — Vol. 1774. — P. 012043, IOP Publishing.

Xu B. and Wang H. (2023). A comparative analysis of adaptive energy management for a hybrid electric vehicle via five driving condition recognition methods. *Energy*. — Vol. 269. P. 126732.

Wan X., Zhang X., and Liu L. (2021). An improved VGG19 transfer learning strip steel surface defect recognition deep neural network based on few samples and imbalanced datasets // *Applied Sciences*. — Vol. 11. — No. 6. P. 2606.

Wang H., Li K., and Xu C. (2022). A new generation of ResNet model based on artificial intelligence and few data driven and its construction in image recognition model // *Computational Intelligence and Neuroscience*. No. 13. Pp. 1–10.

Wei J., and Ju Y. (2024). Research on optimization method for traffic signal control at intersections in smart cities based on adaptive artificial fish swarm algorithm. *Heliyon*. — Vol. 10. — No. 8. p. e30657. DOI:10.1016/j.heliyon.2024.e30657.

Zhang L., Leng X., Feng S., Ma X., Ji K., Kuang G., and Liu L. (2024). Optimal azimuth angle selection for limited SAR vehicle target recognition // *International Journal of Applied Earth Observation and Geoinformation*. — Vol. 128. P. 103707.

**INTERNATIONAL JOURNAL OF INFORMATION AND
COMMUNICATION TECHNOLOGIES**

**ХАЛЫҚАРАЛЫҚ АҚПАРАТТЫҚ ЖӘНЕ КОММУНИКАЦИЯЛЫҚ
ТЕХНОЛОГИЯЛАР ЖУРНАЛЫ**

**МЕЖДУНАРОДНЫЙ ЖУРНАЛ ИНФОРМАЦИОННЫХ И
КОММУНИКАЦИОННЫХ ТЕХНОЛОГИЙ**

Собственник:

АО «Международный университет информационных
технологий» (Казахстан, Алматы)

Главный редактор:

Колесникова Катерина Викторовна

Ответственный редактор:

Мрзабаева Раушан Жалиевна

Компьютерная верстка:

Калабай Замзагуль Ертугановна

Сайт журнала: <https://journal.iitu.edu.kz>

ISSN 2708–2032 (print)

ISSN 2708–2040 (online)

Подписано в печать 30.03.2026.

050040 г. Алматы, ул. Манаса 34/1, каб. 709, тел: +7 (727) 244-51-09).