необходимо их нормализовать и привести к единой системе. итоговое значение индекса комплексно отражает общее геоэкологическое состояние территории. В настоящее время в международном масштабе разработано множество индексных систем, таких как Environmental Performance Index (EPI), City Sustainability Index, Ecological Footprint, [12] которые различаются своими подходами и методами.

Многокритериальный анализ (Multi-Criteria Analysis) основанный на инструментах теории принятия решений, позволяет проводить комплексную оценку систем с множеством показателей. С помощью методов MCDM (Multi-Criteria Decision Making) [5]можно анализировать геоэкологическое состояние территории на основе нескольких критериев.

Например, чтобы оценить город как экологически благоприятный, необходимо высокое качество воздуха, воды и зеленых зон, но для определения, какой из них имеет преобладающее значение, требуется многокритериальный анализ.

В этом методе на основе мнений экспертов критериям присваиваются веса, а затем варианты оцениваются через эти веса. На практике широко применяются такие методы, как Аналитический иерархический процесс (AHP), TOPSIS, EVAMIX[12].

Сначала строится иерархия критериев оценки: например, под «Экологическим состоянием» находятся критерии «Воздух», «Вода», «Почва», под которыми размещаются определяющие индикаторы ($PM_{2.5}$, BHM_5,количество тяжелых металлов и др.)[5].

Затем эксперты определяют важность каждого критерия (например, качество воздуха считается наиболее важным критерием для здоровья человека). В результате формируются баллы по каждому критерию и получается интегрированная итоговая оценка.

Основное преимущество многокритериального анализа - он делает процесс прозрачным и адаптивным. Например, если критерию «доля зеленых насаждений» придать большее значение, общий рейтинг города с большим количеством садов и парков резко возрастет.

Сегодня этот метод получает дальнейшее развитие в интеграции с ГИС-технологиями[10]. Особенно пространственный многокритериальный анализ становится важным инструментом в территориальном планировании, позволяя оптимизировать решения на основе карт.

Заключение. Согласно результатам исследования, хотя многие ученые использовали различные методы для оценки геоэкологического состояния урбанизированных территорий, мы можем выделить рейтинговую оценку, оценку на основе индексов и методы многокритериального анализа как обобщающие и наиболее совершенные.

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AI-SUPPORTED EARLY ALZHEIMER'S DISEASE IDENTIFICATION

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Annotation: We review current methods, datasets, and translational milestones including the first FDA-cleared blood-based test for AD pathology and propose best practices and a roadmap for clinical adoption of AI-assisted early detection.

Keywords: Alzheimer's disease, early detection, artificial intelligence, machine learning, biomarkers, neuroimaging, explainable AI, multimodal fusion.

РАННЯЯ ДИАГНОСТИКА БОЛЕЗНИ АЛЬЦГЕЙМЕРА С ПОДДЕРЖКОЙ ИИ

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Аннотация: В статье рассматриваются современные методы, наборы данных и ключевые достижения трансляционных исследований, включая первый одобренный FDA анализ крови для определения патологии AD, а также предлагаются лучшие практики и «дорожная карта» для внедрения технологий AI в клиническую диагностику ранних стадий заболевания.

Ключевые слова: болезнь Альцгеймера, раннее выявление, искусственный интеллект, машинное обучение, биомаркеры, нейровизуализация, интерпретируемый ИИ, мультимодальная интеграция.

СУНЪИЙ ИНТЕЛЛЕКТ ЁРДАМИДА АЛЦГЕЙМЕР КАСАЛЛИГИНИ ЭРТА АНИҚЛАШ

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Annotatsiya: Maqolada amaldagi usullar, ma'lumotlar to'plamlari, targ'ibot sohasidagi yutuqlar, shu jumladan AD patologiyasini aniqlash bo'yicha FDA tomonidan tasdiqlangan birinchi qon testi ko'rib chiqiladi hamda AI yordamida erta aniqlashni klinik amaliyotga joriy etish uchun eng yaxshi tajribalar va "yo'l xaritasi" taklif etiladi.

Kalit so'zlar: Alsgeymer kasalligi, erta aniqlash, sun'iy intellekt, mashina o'rganish, biomarkerlar, neyrovizualizatsiya, izohlanadigan AI, multimodal integratsiya.

1. Introduction. Alzheimer's disease is a progressive neurodegenerative disorder characterized pathologically by accumulation of amyloid-β (Aβ) plaques and tau neurofibrillary tangles. Early (preclinical/prodromal) detection is essential for patient selection for therapies and for better prognostication. Traditional diagnostics (clinical exam, PET imaging, CSF assays) are informative but costly, invasive, or not widely available. AI approaches leverage patterns in multimodal data to detect disease signals earlier and at scale. Recent regulatory and biomarker advances (e.g., FDA clearance of the Lumipulse plasma p-tau217/Aβ1-42 ratio) mark inflection points toward clinical utility.

2. Background & rationale

2.1 Biological markers and modalities

- **Neuroimaging**: Structural MRI shows regional atrophy (e.g., hippocampus); FDG-PET measures hypometabolism; amyloid and tau PET provide direct pathology imaging.
- **Biofluid biomarkers**: Plasma p-tau217 and p-tau181, neurofilament light (NfL), and glial fibrillary acidic protein (GFAP) are emerging as scalable blood tests with strong predictive value for future AD dementia. Combining plasma p-tau217 with other markers improves predictive power.
- **Cognitive and clinical assessments**: Composite neuropsychological tests and digital cognitive assessments remain important inputs for model training.

Biomarker	Analyte Type	Analytical Method	Diagnostic Role	AI Integration Potential
p-tau217	Phosphorylated tau protein	Immunoassay / mass spectrometry	Strong early marker of tau pathology	High — numeric input for ML models
Aβ42 / Aβ40 ratio	Amyloid-β peptides	Immunoassay	Early amyloid accumulation	Moderate — useful with tau
Neurofilament Light Chain	Axonal injury marker	SIMOA / ELISA	Neurodegeneration indicator	High — adds non-specific

(NfL)				neurodegeneration info
GFAP	Astrocytic activation	SIMOA	Reflects neuroinflammation	High — improves model discrimination
p-tau181	Phosphorylated tau	Immunoassay	Early to mid-stage marker	Moderate — supports staging

Table-1: Summary of Blood Biomarkers in Early Alzheimer's Detection

2.2 Why AI?

AI models, particularly convolutional neural networks (CNNs) and transformer-based architectures, can detect subtle patterns across pixels/voxels and non-linear interactions in multimodal data that elude human readers. Machine learning can also integrate heterogeneous feature types (imaging, fluid biomarker values, demographics, genetics) to produce individualized risk scores. Recent studies have shown promising classification and prognostic performance when trained on large longitudinal cohorts.

3. Datasets & Resources

Widely used public datasets and consortia for model development and validation include:

- **Alzheimer's Disease Neuroimaging Initiative (ADNI)** longitudinal MRI/PET/CSF/plasma, cognitive data; primary resource for training and benchmarking.
- OASIS, UK Biobank (for population imaging), local clinical cohorts, and biobanks used for external validation.

Best practice: train on a large diverse multicenter dataset (ADNI + others) and perform external validation across geographic sites to assess generalizability.

Dataset	Modalities Included	Sample Size	Data Type	Accessibility	Notes / Usage
ADNI (Alzheimer's Disease Neuroimaging Initiative)	MRI, PET, CSF, plasma, cognitive	~2,000+	Longitudinal	Public (application required)	Benchmark dataset for AD AI models
OASIS-3	MRI, PET, cognitive	~1,000	Cross-sectional + longitudinal	Public	Used for validation and transfer learning
UK Biobank	MRI, genetics, health records	500,000	Population imaging	Public (restricted access)	Used for generalization testing
AIBL	MRI, PET, plasma biomarkers	~1,100	Longitudinal	Application	Focused on early AD and aging
MIRIAD	MRI only	~100	Longitudinal	Open	Compact dataset for model prototyping

Table-2: Key Public Datasets Used in AI-based Alzheimer's Research

4. Methods - Ai approaches for early ad detection

4.1 Preprocessing

- Standard MRI preprocessing: skull-strip, registration to standard space, bias correction, segmentation (GM/WM/CSF), region-of-interest extraction.
- PET preprocessing: attenuation correction, SUVR calculation, partial volume correction when available.
- Biomarker harmonization: laboratory assay calibration, ratio computations (e.g., p-tau217/Aβ1-42), and batch effect correction.

4.2 Model families

- **Classical ML**: Random forests, gradient boosting machines on engineered features (volumes, cognitive scores, biomarker values).
- **Deep learning**: 2D/3D CNNs on raw images; recurrent networks for longitudinal sequences; multimodal fusion architectures that combine imaging branches with tabular branches for biomarkers and demographics.

• **Hybrid & transfer learning**: Pretrained encoders (e.g., ImageNet → MRI fine-tuning) and domain adaptation techniques to handle scanner/site variability.

Technique	Data Modality	Description / Model Type	Key Advantages	Limitations	Reported Accuracy (AUC / F1)
Random Forest / XGBoost	MRI volumetric, cognitive scores	Classical ML on handcrafted features	Fast, interpretable, low computation	Limited nonlinearity capture	0.80–0.85
3D Convolutional Neural Networks (CNNs)	MRI / PET	Deep hierarchical spatial learning	Learns features automatically, strong imaging power	Needs large dataset, high computation	0.88–0.93
Recurrent Neural Networks (RNNs) / LSTMs	Longitudinal MRI + clinical	Captures temporal disease progression	Handles time-series well	Risk of overfitting on short sequences	0.82–0.90
Transformer / Attention models	MRI + plasma biomarkers + clinical	Integrates multimodal embeddings	Handles complex relationships	Requires large multimodal data	0.90–0.95
Graph Neural Networks (GNNs)	Brain connectivity networks (fMRI, DTI)	Models spatial-functional relationships	Explains regional interactions	Complex, less standardized	0.85–0.92

Table-3: Comparison of Major AI Techniques Used for Early Alzheimer's Detection

4.3 Multimodal fusion strategies

• Early fusion (concatenate features at input), intermediate fusion (combine modality-specific embeddings), or late fusion (ensemble predictions). Multimodal models often outperform unimodal ones in predicting amyloid/tau PET status or cognitive conversion.

4.4 Interpretability & explainability

• Post-hoc XAI methods (Grad-CAM, integrated gradients, SHAP for tabular) and inherently interpretable models (attention mechanisms, sparse models) improve clinician trust. Multiple reviews emphasize that lack of interpretability is a major barrier to clinical adoption.

5. Literature synthesis - Key findings

5.1 Performance of AI models

• Models combining MRI + cognitive scores + plasma biomarkers show highest AUCs for classifying AD vs controls and predicting conversion from MCI to AD. Several recent reviews report steady improvements in sensitivity and specificity when multimodal inputs are used.

5.2 Blood biomarkers and AI: a turning point

• The FDA's 2025 clearance of the Lumipulse G pTau217/β-Amyloid 1-42 plasma ratio marks a practical shift: validated plasma assays can be included as trusted inputs for AI models, improving noninvasive screening and triage for confirmatory PET/CSF testing. Large studies show plasma p-tau217 (and combined ratios) discriminate AD pathology with high negative predictive value and improving positive predictive value when combined with other markers.

5.3 Explainable AI uptake

• Growth in XAI studies for AD detection has been substantial; however, most methods remain post-hoc and are not yet standardized for clinical explanation. Reviews call for dedicated AD-specific interpretability datasets and clinical-grade reporting standards.

6. Discussion

6.1 Opportunities

• **Scalability:** Blood biomarkers enable population-scale screening; AI risk scores can triage patients to specialized centers for PET/CSF confirmation.

• **Personalized prognosis:** Longitudinal AI models can forecast rate of cognitive decline, aiding individualized care planning and trial enrichment.

6.2 Challenges

- **Data bias & generalizability:** Overreliance on ADNI and other Western cohorts risks model bias; external validation across ethnicities, scanner vendors, and healthcare systems is necessary.
- **Clinical validation & regulatory pathway:** While biomarkers are advancing (FDA clearance for Lumipulse), AI models themselves often lack robust prospective clinical trials demonstrating impact on care decisions and outcomes. Regulatory frameworks require transparent performance reporting and bias mitigation.
- **Interpretability and clinician trust:** Clinicians need simple, reliable explanations of model outputs; integration with workflows (EHRs) and human-in-the-loop systems are required.
- **Ethics & privacy:** Predicting future dementia raises consent, disclosure, and psychosocial concerns. Policies for counseling, data governance, and handling uncertain predictions must be established.

6.3 Proposed best practices

1. **Multimodal development** - combine imaging, plasma biomarkers, and cognitive tests.
2. **Large, diverse training cohorts + external validation** across geographic and clinical settings.
3. **Prospective clinical trials** to demonstrate clinical utility (does AI triage improve outcomes or decision quality?).
4. **Implement XAI** standards: report what features contributed to a decision, expected model uncertainty, and failure modes.
5. **Regulatory alignment**: engage early with regulators and use validated biomarkers (FDA-cleared assays) as inputs where possible.

7. Conclusion

AI-assisted early detection of Alzheimer's disease is rapidly maturing. The combination of robust plasma biomarkers (e.g., p-tau217/Aβ ratios), large multimodal datasets (e.g., ADNI), and advanced ML models provides a realistic path toward scalable, noninvasive screening and risk stratification. To translate models into clinical practice, researchers must prioritize external validation, explainability, prospective impact trials, and ethical frameworks. The recent regulatory milestone of an FDA-cleared blood test (May 16, 2025) materially improves the feasibility of AI-driven screening and triage pathways.

8. Future directions (Research roadmap)

- **Multicenter prospective trials** comparing AI + blood biomarkers vs standard of care for diagnostic yield and outcomes.
- **Federated learning frameworks** to pool data across institutions while preserving privacy.
- **Clinical decision support (CDS) studies** to embed AI outputs within oncology-style multidisciplinary workflows (neurology + geriatrics + neuropsychology).
- **Standardized XAI reporting** and creation of AD-specific interpretability benchmarks.
- **Economic evaluations** to assess cost-effectiveness of AI-driven screening in healthcare systems.

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ИНТЕЛЛЕКТУАЛЬНЫЕ ПРОИЗВОДСТВЕННЫЕ СИСТЕМЫ ИЦИФРОВЫЕ ДВОЙНИКИ

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Аннотация: В статье рассматриваются концепции интеллектуальных производственных систем (ИПС) и цифровых двойников (ЦД) как ключевых драйверов парадигмы индустрии 4.0. Анализируется их роль в повышении эффективности, гибкости и устойчивости промышленных процессов. Особое внимание уделяется интеграции этих технологий для создания самооптимизирующихся производственных сред, способных к прогнозированию сбоев, моделированию «что-если» сценариев и принятию автономных решений.

Ключевые слова: интеллектуальные производственные системы, цифровой двойник, индустрия 4.0, производственные технологии, искусственный интеллект, оптимизация производства.

INTELLIGENT MANUFACTURING SYSTEMS AND DIGITAL TWINS

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Annotation: This article examines the concepts of Intelligent Manufacturing Systems (IMS) and Digital Twins (DT) as key drivers of the Industry 4.0 paradigm. Their role in enhancing the efficiency, flexibility, and sustainability of industrial processes is analyzed. Special attention is given to the integration of these technologies to create self-optimizing production environments capable of predicting failures, modeling "what-if" scenarios, and making autonomous decisions.

Keywords: intelligent manufacturing systems (IMS), digital twin (DT), ndustry 4.0, production technologies, artificial intelligence (AI), manufacturing optimization.

INTELLEKTUALISHLAB CHIQARISH TIZIMLARI VA RAQAMLI EGIZAKLAR

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Annotatsiya: Maqolada intellektual ishlab chiqarish tizimlari (IIT) va raqamli egizaklar (RE) tushunchalari sanoat 4.0 paradigmasining asosiy harakatlantiruvchi kuchlari sifatida ko‘rib chiqiladi. Ularning sanoat jarayonlari samaradorligini, moslashuvchanligini va barqarorligini oshirishdagi roli tahlil qilinadi. E’tibor, nosozliklarni bashorat qilish, "agar shunday bo‘lsa" ssenariylarini modellashtirish va avtonom qarorlar qabul qilishga qodir bo‘lgan o‘z-o‘zini optimallashtiruvchi ishlab chiqarish muhitlarini yaratish uchun ushbu texnologiyalarni integratsiyalashga qaratilgan.

Kalit so‘zlar: intellektual ishlab chiqarish tizimlari, raqamli egizak, sanoat 4.0, ishlab chiqarish texnologiyalari, sun’iy intellekt, ishlab chiqarishni optimallashtirish.