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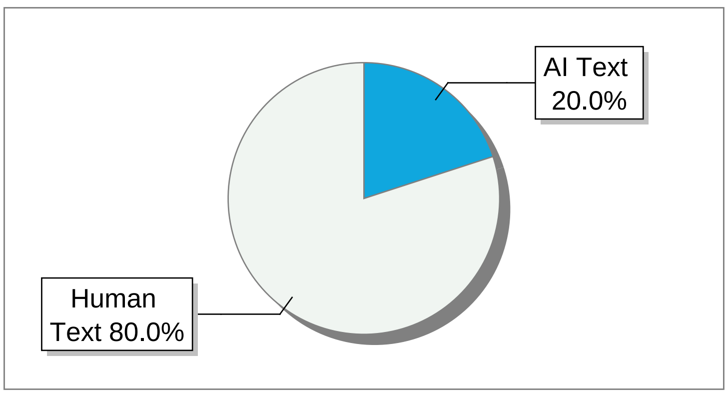

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A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 1 TJIT Department of MCA 2024-2025 ABSTRACT Chronic Kidney Disease (CKD) is a major health concern that often remains undiagnosed until its later stages, leading to severe complications.
The risk is even higher among individuals living with Human Immunodeficiency Virus (HIV), as both the infection and the long-term use of antiretroviral therapy can adversely affect kidney function.
Early identification of CKD stages in HIV-infected patients is therefore crucial for timely treatment and improved quality of life.
Recent advances in machine learning (ML) provide promising solutions for healthcare, as these models can analyse large medical datasets, detect hidden patterns, and accurately classify disease stages.
This study focuses on developing a machine learning-based approach for predicting and classifying CKD stages in HIV patients.
By utilizing clinical parameters such as serum creatinine, eGFR, blood urea levels, and other biochemical markers, the proposed model aims to assist clinicians in early diagnosis and risk assessment.
Such an approach not only supports precision medicine but also helps reduce the burden on healthcare systems by enabling preventive care and personalized treatment strategies.
A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 2 TJIT Department of MCA 2024-2025 CONTENT PAGE A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 3 TJIT Department of MCA 2024-2025 1-INTRODUCTION Chronic Kidney Disease (CKD) is a progressive disorder in which the kidneys gradually lose their ability to filter waste and regulate fluid balance in the body.
It affects millions of people worldwide and is considered a silent condition, as symptoms often appear only in the advanced stages.
Among people living with Human Immunodeficiency Virus (HIV), the risk of developing CKD is significantly higher.
This is due to multiple factors such as the direct impact of the virus on kidney tissues, opportunistic infections, and the long-term effects of antiretroviral therapy.
If not detected early, CKD in HIV-infected individuals can lead to severe health complications, including end-stage renal disease, which requires dialysis or kidney transplantation.
In recent years, machine learning (ML) has emerged as a powerful tool in the healthcare domain.
Unlike traditional diagnostic methods, ML algorithms can process large amounts of clinical data, identify subtle patterns, and provide accurate predictions that may not be easily recognized by human observation.
Applying ML to predict and classify CKD stages in HIV patients offers a valuable opportunity to support clinicians in making timely decisions.
By analysing parameters such as serum creatinine, eGFR, blood pressure, and other laboratory values, ML-based systems can help in early risk detection, stage classification, and continuous monitoring.
This research aims to explore how machine learning can be effectively used to identify CKD stages in HIV-infected patients, thereby enhancing early diagnosis, improving treatment outcomes, and reducing the overall burden on healthcare systems.
11 PROJECT OVERVIEW Chronic Kidney Disease (CKD) remains a silent yet progressive health challenge, especially among patients living with HIV, where the risk of kidney damage is amplified by both the infection and long-term antiretroviral therapy.
Early and accurate identification of CKD stages in these patients can significantly improve treatment outcomes and prevent irreversible complications.
Traditional diagnostic methods, although effective, often fail to detect subtle patterns in complex medical data.
To address this gap, this project applies the Support Vector Machine (SVM) algorithm, a powerful supervised machine learning technique, to classify and predict CKD stages in HIV- infected patients.
SVM is well-suited for healthcare data because it can handle high-dimensional inputs, identify non-linear relationships, and provide reliable classification results.
In this project, clinical features such as estimated Glomerular Filtration Rate (eGFR), serum creatinine, blood urea, and other biochemical parameters are used as input data.
The SVM model is trained to distinguish between different CKD stages, enabling timely identification of patients at risk.

A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 4 TJIT Department of MCA 2024-2025 By implementing SVM, the project aims to create an intelligent decision-support tool that assists healthcare professionals in diagnosing CKD more accurately and at earlier stages.
This not only enhances patient care but also supports personalized treatment planning and reduces the overall healthcare burden.
Support Vector Machine learning Support Vector Machine (SVM) is a powerful supervised learning algorithm widely used for medical data classification, and its advanced learning techniques make it particularly suitable for complex problems like identifying chronic kidney disease (CKD) stages in HIV-infected patients.
Unlike basic classifiers, advanced SVMs apply concepts such as soft margin optimization, kernel functions, and cost-sensitive learning to deal with noisy clinical data, nonlinear relationships, and imbalanced class distributions.
The use of kernel tricks, especially the radial basis function (RBF), helps capture hidden patterns between clinical parameters such as eGFR, serum creatinine, and blood urea levels, while soft margin control (through the regularization parameter C) ensures a balance between accuracy and generalization.
To address the ordinal nature of CKD stages, extended approaches like ordinal SVMs or regression-based threshold mapping can be used, ensuring predictions respect the natural order of disease progression.
Additionally, probability calibration techniques such as Platt scaling or isotonic regression transform raw outputs into reliable risk scores, making the model more clinically interpretable.
Handling imbalanced data through methods like SMOTE or class-weight adjustments ensures that rare advanced stages are not overlooked, while explainability tools such as SHAP or LIME can provide transparency for clinicians by highlighting which features influence a prediction.
With proper feature preprocessing, hyperparameter tuning, and validation strategies, an advanced SVM framework can serve as a robust decision-support system, enabling early CKD detection and stage classification in HIV patients, ultimately improving treatment planning and patient outcomes.
111 Support Vector Machines (SVM) A clinical rule engine is a decision-support mechanism that applies predefined medical rules and knowledge to patient data in order to assist healthcare professionals in making accurate diagnoses and treatment decisions.
When combined with machine learning, it becomes more powerful, as it can integrate both expert medical guidelines and data-driven insights.
In the context of chronic kidney disease (CKD) identification in HIV-infected patients, a clinical rule engine works by translating established medical thresholds such as eGFR ranges, serum creatinine levels, and blood pressure limits into rules that guide classification.
For example, if the eGFR value is below 60 mL/min/173m² for more than three months, the system can automatically flag the case as indicative of CKD.
Machine learning models, such as Support A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 5 TJIT Department of MCA 2024-2025 Vector Machines (SVM), then enhance this rule-based framework by detecting hidden patterns and refining predictions beyond what fixed rules alone can achieve.
The integration of a clinical rule engine ensures that the system's predictions remain aligned with medical standards while also benefiting from the adaptability of machine learning.
This hybrid approach not only increases accuracy but also builds trust among clinicians, as it provides transparent reasoning behind predictions.
Ultimately, such a system supports early CKD stage detection, reduces the chances of misdiagnosis, and helps in delivering personalized care to HIV-infected patients.
112 Intelligent Machine Learning Pipeline An intelligent machine learning (ML) pipeline is a structured workflow that automates the process of turning raw healthcare data into meaningful predictions and decisions.
For identifying chronic kidney disease (CKD) stages in HIV-infected patients, such a pipeline ensures accuracy, reliability, and clinical usefulness.
The process begins with data collection, where medical records containing features such as eGFR, serum creatinine, blood urea, and other clinical parameters are gathered.
This raw data often contains missing values, noise, or inconsistencies, so the next step is data preprocessing.
Here, techniques like data cleaning, normalization, and handling of outliers are applied to ensure high-quality

inputs.
Once cleaned, the data moves to feature selection and engineering, where the most relevant attributes that impact CKD progression are identified.
This reduces complexity and enhances the efficiency of the model.
The refined dataset is then fed into the Support Vector Machine (SVM) classifier, which serves as the core learning algorithm.
SVM analyzes the patient data, learns hidden patterns, and classifies the CKD stages with high precision.
To ensure robustness, the pipeline includes model evaluation using metrics such as accuracy, sensitivity, specificity, and F1-score.
Continuous refinement is carried out by hyperparameter tuning and cross-validation.
Finally, the predictions are integrated into a decision-support system, enabling healthcare providers to detect CKD early, recommend personalized treatments, and monitor disease progression in HIV patients.
This intelligent ML pipeline not only automates the analysis but also bridges the gap between raw clinical data and actionable medical insights, ultimately supporting better healthcare outcomes.
11 3 Clinical Intelligence Clinical Intelligence refers to the process of using data-driven insights to improve healthcare decision-making, patient outcomes, and operational efficiency in medical settings.
It A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 6 TJIT Department of MCA 2024-2025 combines advanced technologies like machine learning, artificial intelligence, and data analytics with clinical expertise to extract meaningful information from vast amounts of healthcare data, including patient records, laboratory results, and diagnostic reports.
In the context of chronic kidney disease (CKD) in HIV-infected patients, clinical intelligence can help identify early warning signs, predict disease progression, and recommend personalized treatment plans.
For example, by analysing trends in laboratory values such as serum creatinine, eGFR, and blood urea, clinical intelligence tools can alrt doctors to subtle changes that may indicate worsening kidney function.
This approach not only supports timely interventions but also enhances the efficiency of healthcare delivery by prioritizing high-risk patients and reducing the chances of misdiagnosis.
Ultimately, clinical intelligence bridges the gap between raw medical data and actionable knowledge, enabling healthcare professionals to make more informed, accurate, and timely decisions, while improving patient care and optimizing resource allocation.
114 Understanding Images Using Support Vector Machine Support Vector Machine (SVM) is a supervised machine learning algorithm primarily used for classification tasks.
When it comes to images, SVM can be applied to recognize patterns, detect objects, or classify images into different categories based on their features.
Instead of analyzing the raw pixels directly, images are first converted into a set of measurable characteristics such as color histograms, textures, edges, or shapes, which serve as the input features for the SVM model.
SVM works by finding the best boundary, known as a hyperplane, that separates different image classes in a high-dimensional feature space.
For instance, if the task is to distinguish between images of healthy kidneys and those affected by disease, SVM identifies the optimal dividing line (or hyperplane) that maximizes the separation between these two classes.
Kernel functions, such as linear, polynomial, or radial basis function (RBF), allow SVM to handle complex, non-linear relationships in the image data.
Using SVM for image understanding is highly effective because it can deal with high-dimensional data, provides robust classification even with limited training samples, and is resistant to overfitting.
This makes it an ideal choice for medical imaging, object recognition, and other image- based classification problems where accuracy and reliability are crucial.
115 Hyperparameter Tuning While recent advancements in DL have mainly been driven by supervised learning, unsupervised learning is expected to become increasingly important in the future.
Much like humans and animals, who learn mainly by observation rather than explicit labeling of every object, future deep learning systems may rely more on unsupervised methods to acquire knowledge and A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 7 TJIT Department of MCA 2024-2025 recognize patterns from dataSimilarly, human vision functions as an active process, combining a high-resolution central focus (fovea) with a wider, lower-resolution periphery to intelligently sample the visual field.

This highlights the potential of unsupervised and self-supervised methods to drive the next generation of deep learning systems by more closely mirroring natural learning processes.
117 ML in Contrast to Futuristic Programming Machine Learning (ML) represents a paradigm shift in how software interacts with data and solves problems.
Unlike traditional programming, where developers explicitly write step-by-step instructions to achieve a desired outcome, ML systems learn patterns from historical data and make predictions or decisions without being explicitly programmed for every scenario.
This capability makes ML highly adaptive, especially in handling complex, high-dimensional, and dynamic datasets that are difficult to manage through conventional coding techniques.
For example, in healthcare, ML models can analyze vast amounts of patient data to identify early signs of diseases, a task that would be tedious and error-prone using classical programming approaches.
Futuristic programming, on the other hand, envisions a next-generation coding paradigm where software evolves toward autonomous, self-optimizing, and context-aware systems.
In this approach, programs are designed to anticipate user needs, adapt to changing environments, and even improve themselves over time.
While ML is a key enabler of this vision, futuristic programming extends beyond predictive analytics to incorporate real-time reasoning, natural language understanding, and cognitive decision-making.
Essentially, ML provides the learning and prediction backbone, whereas futuristic programming integrates this intelligence into fully autonomous and human-like software systems.
In contrast to the deterministic nature of traditional programming, both ML and futuristic programming embrace uncertainty, continuous improvement, and adaptability.
However, ML is typically task-specific and data-driven, whereas futuristic programming emphasizes holistic autonomy, multi-domain intelligence, and seamless human-computer collaboration.
As computing progresses, the convergence of these approaches promises software that is not only predictive and analytical but also anticipatory, contextually aware, and capable of making complex decisions with minimal human intervention.
This evolution highlights a significant shift in software development from manually coded logic to intelligent systems capable of learning, adapting, and innovating on their own.
A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 8 TJIT Department of MCA 2024-2025 Fig1 Shows traditional Programming Machine Learning (ML) represents a paradigm shift from futuristic programming approaches, where explicit instructions are written for a computer to follow.
In conventional programming, a developer must define every rule and logic for the system to function, which can be limiting when handling complex or dynamic data.
In contrast, ML enables computers to learn from data and improve over time, identifying patterns, making predictions, and adapting without explicit programming for every scenario.
Futuristic programming, often associated with AI-driven or autonomous systems, takes this concept further by incorporating self-learning, reasoning, and decision-making capabilities, allowing machines to perform tasks that were once considered purely human.
While ML focuses primarily on data-driven learning and predictive modeling, futuristic programming envisions systems that can understand context, simulate reasoning, and evolve autonomously, bridging the gap between human intelligence and computational power.
This progression is transforming industries such as healthcare, finance, and autonomous vehicles, where adaptive systems can make informed decisions faster, more accurately, and with minimal human intervention.
By integrating ML as a foundation, futuristic programming promises not only efficiency but also the creation of intelligent systems capable of continuous innovation.
Fig2 Shows Machine Learning A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 9 TJIT Department of MCA 2024-2025 118 HOW DOES MACHINE LEARNING WORK IN CKD?
Machine learning (ML) has emerged as a transformative tool in healthcare, particularly for the early detection and management of chronic kidney disease (CKD).
In CKD, timely identification of the disease stage is crucial to prevent irreversible kidney damage and improve patient outcomes.
ML works by analysing large volumes of patient data, including clinical measurements such as serum creatinine,

blood urea, estimated Glomerular Filtration Rate (eGFR), protein levels, blood pressure, age, and other relevant health parameters.

The process begins with data collection, where medical records and laboratory test results are gathered.

Next, the data undergoes preprocessing, which involves cleaning, handling missing values, and normalizing features to ensure accurate analysis.

Important variables are then selected, often through feature selection techniques, to identify the most relevant indicators of CKD progression.

Machine learning models, such as Support Vector Machines (SVM), Random Forests, or Neural Networks, are then trained on this data to learn patterns and relationships that might not be easily visible to humans.

Once trained, the ML model can classify patients into different CKD stages ranging from mild to severe based on their clinical parameters.

This enables early diagnosis, personalized treatment recommendations, and continuous monitoring of disease progression.

Moreover, machine learning models can improve over time as more data becomes available, making them increasingly accurate and reliable.

By automating pattern recognition and risk prediction, ML helps doctors make informed decisions faster, reduces human error, and ultimately enhances patient care.

Fig 3Shows Learning Phase 1191 Deducing Chronic Kidney Disease (CKD) is a progressive condition that affects kidney function over time, and its occurrence is notably higher among patients living with HIV due to the combined effects of the virus, long-term medication, and other health complications.

Early detection of CKD A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 10 TJIT Department of MCA 2024-2025 stages in such patients is crucial because it enables timely intervention, improves quality of life, and reduces the risk of severe outcomes like kidney failure.

Machine Learning (ML) techniques are increasingly being explored as effective tools to identify and classify the stages of CKD with greater accuracy.

By analysing medical records, lab test results, and patient health indicators, ML models can detect hidden patterns that traditional diagnostic methods might miss.

This approach not only supports healthcare professionals in making more reliable decisions but also helps in tailoring treatment plans specific to the needs of HIV-infected patients, thereby enhancing patient care and long-term management.

Fig 4Shows Learning Phase Supervised and unsupervised learning are the two broad categories into which machine learning can be divided.

In labelled-data learning, an algorithm learns the relationship between input features and output labels from training data, frequently with help or feedback.

For instance, a business analyst may forecast sales by taking into account variables like weather and marketing costs.

This method can be used to predict results for new, unseen data when the outputs are known.

Additionally, labelled-data learning can be divided into two main categories.

1Classification chronic kidney disease (CKD) in people living with HIV can be classified into several categories based on its underlying causes.

One of the most recognized forms is HIV-associated nephropathy (HIVAN), which occurs as a direct result of the virus and often presents with proteinuria, enlarged kidneys, and rapid progression to kidney failure, especially in individuals of African descent due to genetic risk factors.

Another type is HIV-related immune complex kidney disease, which develops when the immune system reacts abnormally to the virus, leading to immune deposits in the kidney and causing glomerulonephritis with symptoms such as blood and protein in the urine.

In addition to disease caused directly by HIV, antiretroviral therapy (ART) can also contribute to kidney damage, with drugs like tenofovir and some protease inhibitors linked to tubular dysfunction, electrolyte imbalance, and gradual decline in kidney function.

Beyond HIV-specific causes, traditional CKD risk factors such as diabetes, hypertension, hepatitis coinfections, and cardiovascular disease play a major role, but the presence of HIV tends to worsenA Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 11 TJIT Department of MCA 2024-

2025 their impact and accelerate kidney damage.
Lastly, opportunistic infections and HIV-related cancers can also involve the kidneys, leading to either acute or chronic impairment.
Overall, CKD in HIV-infected patients is a multifactorial condition that requires careful classification for effective diagnosis and managements.
Regression Chronic kidney disease (CKD) is a major health concern among individuals living with HIV, as the infection and long-term antiretroviral therapy can accelerate kidney damage.
Early detection of CKD stages is crucial to prevent complications and improve patient outcomes.
Machine learning techniques, particularly regression models, play an important role in predicting the progression of CKD by analyzing clinical, biochemical, and demographic data.
Regression helps in mapping the relationship between patient features such as age, viral load, CD4 count, creatinine levels, and estimated glomerular filtration rate (eGFR) with the stages of kidney disease.
By applying linear, logistic, or advanced regression approaches, healthcare providers can obtain accurate stage predictions, enabling timely medical interventions.
This approach not only enhances diagnostic accuracy but also supports personalized treatment planning for HIV-infected patients at risk of kidney dysfunction.
ALGORITHM To build a reliable ML system for identifying CKD stage in patients with HIV, start by collecting a carefully curated dataset that combines routine clinical measurements (eg, eGFR, serum creatinine, urine albumin-to-creatinine ratio), HIV-specific variables (viral load, CD4 count, antiretroviral therapy type and duration), demographics, comorbidities (diabetes, hypertension), and relevant labs and medications.
Clean and harmonize the data by handling missing values with clinically informed imputations, normalizing continuous features, encoding categorical variables, and creating derived features (changes in eGFR over time, cumulative drug exposure) that capture progression patterns.
Because stages are ordered and class imbalance is likely, consider both ordinal-aware models and robust classifiers baseline models like logistic regression (with elastic-net regularization) for interpretability, tree-based ensemble methods such as Random Forest or X G Boost for strong predictive performance, and a light neural network if you have large, longitudinal data.
Use stratified cross-validation and nested hyperparameter tuning to avoid overfitting, apply techniques like SMOTE or class-weighting for imbalance, and evaluate models with clinically meaningful metrics (AUROC, sensitivity/specificity at decision thresholds, and confusion matrices by stage); for ordinal models also report weighted kappa or mean absolute error of predicted stage.
Add explainability (SHAP values or feature-importance plots) so clinicians can see what drives predictions, and validate the chosen model on an external cohort before any clinical use.
Finally, embed privacy safeguards, obtain appropriate approvals, and frame the model as a decision-support tool that complements not replaces clinical judgment, with ongoing monitoring to detect drift as treatment patterns and populations change.
A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 12 TJIT Department of MCA 2024-2025 Fig Shows MachineLearning algorithm.
12 COMPANY PROFILE A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 13 TJIT Department of MCA 2024-2025 2LITERATURE SURVEY 21 Existing System In the current healthcare system, the diagnosis of chronic kidney disease (CKD) in HIV patients mainly depends on traditional clinical examinations, laboratory tests, and physician observations.
Doctors usually monitor parameters such as serum creatinine, glomerular filtration rate (GFR), urine analysis, and blood pressure levels to identify kidney function decline.
While these methods are effective, they are often time-consuming, require repeated testing, and may not detect the disease in its early stages.
In many cases, the progression of CKD in HIV patients goes unnoticed until it reaches an advanced stage, leading to severe complications.
Moreover, manual interpretation of medical data can sometimes result in delayed or inaccurate diagnosis due to human limitations.
Another challenge is that the existing system does not make full use of large amounts of clinical data available in hospitals.

Without advanced tools, patterns hidden in this data remain unexplored.
As a result, there is a lack of predictive accuracy and early detection in current approaches.
This limitation highlights the need for smarter, data-driven techniques that can support doctors in providing timely and precise treatment.
Several notable contributions in this area are as follows [1] J.
A Roth et al.
(2020/2021) Roth and colleagues developed cohort-derived machine-learning models to forecast chronic kidney disease (CKD) onset among people living with HIV.
Their work demonstrates that combining routine clinical records and time-series features allows ML algorithms to flag patients at higher short-term risk of CKD, which could help clinicians prioritize monitoring and preventive care.
PubMed □ S.
K Ghosh et al.
(2023) Ghosh and co-authors proposed a machine-learning driven nomogram to predict early risk of progressing to CKD stages 3–5.
They blended classic clinical predictors with ML selection methods to produce an easy-to-use risk score that clinicians can apply at the bedside, balancing predictive accuracy with interpretability.
PMC □ K.
Takkavatakarn et al.
(2023) Takkavatakarn's team compared several ML models (including ANN, random forest and XGBoost) for predicting progression to end-stage kidney disease.
Their multicenter validation showed these models can perform similarly well and that ensemble or tree-based methods often give robust, clinically useful risk stratification when trained on rich longitudinal datasets.
BioMed Central □ C.
Delrue et al.
(2024) Delrue's narrative review examined the state of ML applications across CKD care, from early detection to prognosis.
The paper emphasizes that while algorithms A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 14 TJIT Department of MCA 2024-2025 can boost detection and personalize follow-up, challenges such as data heterogeneity, external validation and clinician trust remain major barriers to routine use.
PMC □ F.
Khalid (2024) Khalid's systematic review synthesized recent AI/ML studies focused on predicting CKD progression, highlighting which input variables (eg, creatinine, eGFR trends, comorbidities) repeatedly improved model performance.
The author calls for standardized reporting and head-to-head comparisons to understand which architectures generalize best across populations.
PMC □ R.
K Halder et al.
(2024) Halder and collaborators introduced "ML-CKDP," a pipeline emphasizing careful preprocessing and feature selection to improve CKD classification.
Their results show that front-loading data cleaning and dimensionality reduction can materially lift downstream classifier performance a pragmatic reminder that good ML for healthcare is as much about data work as model choice.
ScienceDirect □ S.
K Ghosh et al.
(2024, explainability study) In a study focusing on explainable AI, Ghosh's group used interpretable ML techniques to predict CKD using routine clinical and lab features.
They demonstrate that explainability tools help clinicians understand model drivers (for example, which lab trends matter most), which can increase adoption and reveal plausible biological signals rather than inscrutable black-box rules.
□ M.
A Quayyum (2023) Quayyum's applied study targeted CKD stage classification specifically in HIV-infected

patients and compared deep learning with classical ML approaches.
The work underlines that HIV-specific cohorts can exhibit different risk patterns and that targeted models trained on HIV patient data may outperform general CKD models for this subgroup.
 B.
Metherall et al.
(2025) Metherall and team explored CKD classification and creatinine prediction using varied feature sets (home monitoring, clinic labs).
Their more recent work suggests that integrating at-home monitoring with clinic data can refine stage classification and catch deterioration earlier an important direction for remote care models.
Nature (AIP/June 2024 article) authors on ML for HIV-related CKD prediction A June 2024 article evaluated ML algorithms applied to HIV-related kidney disease and emphasized that models which incorporate HIV-specific variables (like antiretroviral exposure and viral load history) better capture the unique drivers of renal decline in this population.
The paper encourages using HIV-focused features when building CKD staging tools for people living with HIV.
211 Disadvantages of the Existing System ➢ Data Limitations – Machine learning requires large and diverse datasets, but in HIV patients with CKD, high-quality medical data is often limited, incomplete, or inconsistent.
➢ Model Bias – If the dataset is not representative (eg, more from one demographic), the model may produce biased results, leading to unfair or inaccurate predictions.
➢ Interpretability Issues – Many ML models, especially deep learning, work like black boxes, making it hard for doctors to understand the reasoning behind predictions.
A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 15 TJIT Department of MCA 2024-2025 ➢ Need for Clinical Validation – Predictions made by ML must still be validated by medical experts; relying solely on algorithms can risk patient safety.
➢ Resource Intensive – Developing, training, and maintaining ML systems requires strong computational resources, skilled professionals, and continuous monitoring.
➢ Ethical and Privacy Concerns – Patient health data must be handled securely; any breach or misuse could lead to serious ethical and legal issues.
➢ Generalization Challenges – A model trained in one hospital or region may not perform well in another setting due to differences in patient population, treatment protocols, or diagnostic practices.
212 Proposed System The proposed system aims to integrate machine learning (ML) and clinical decision support to improve the early detection, classification, and management of CKD among HIV- infected patients.
The system collects and processes patient data such as demographic details, medical history, laboratory test results (eg, serum creatinine, eGFR, urine protein levels), HIV- specific parameters (CD4 count, viral load), and medication history.
Using these inputs, ML models can predict the stage of CKD, identify patients at higher risk of progression, and suggest appropriate treatment adjustments.
The framework is designed to work in three steps Data Collection & Preprocessing – Gathering clinical and laboratory data of HIV patients, cleaning it, and converting it into a usable format for analysis.
ML-Based Prediction & Classification – Applying algorithms (eg, Random Forest, SVM, or Neural Networks) to classify CKD stages and highlight potential risk factors.
Clinical Decision Support – Providing recommendations for treatment options such as adjusting ART regimens to reduce nephrotoxicity, controlling blood pressure, or managing diabetes and hypertension if present.
2121 Advantages of the Presented System ➢ Early Detection Helps identify CKD in its initial stages, even before severe symptoms appear, improving chances of timely intervention.
➢ Personalized Care Supports doctors in tailoring treatment plans based on individual risk profiles and comorbidities.
➢ Prevention of Drug Toxicity Detects potential nephrotoxic effects of antiretroviral drugs, allowing safer medication choices.
➢ Improved Accuracy ML algorithms reduce human error in diagnosis and classification by analysing large datasets more efficiently.

➢ Better Patient Outcomes By predicting disease progression, the system allows proactive management, slowing CKD progression and reducing complications.
A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 16 TJIT Department of MCA 2024-2025 ➢ Resource Optimization Minimizes unnecessary tests and hospital visits by providing precise recommendations, which is especially valuable in resource-limited healthcare settings.
22 Feasibility Study The feasibility of studying and managing chronic kidney disease (CKD) among HIV-infected patients depends on multiple clinical, technical, and practical factors.
Since CKD is a rising comorbidity in this group, such a study is not only relevant but also highly valuable for improving patient care.
221 Clinical Feasibility CKD is common among people living with HIV due to direct effects of the virus, immune- mediated damage, long-term use of antiretroviral therapy, and co-existing conditions like hypertension or diabetes.
Early detection through routine screening (urine protein levels, serum creatinine, and estimated GFR) is practical in most healthcare settings.
With ART widely available, patients are living longer, making CKD a growing clinical challenge that is feasible to study within this population.
222 Technical Feasibility Standard laboratory tests and imaging techniques to diagnose CKD are already established and accessible in most medical centers.
Moreover, machine learning and AI-based prediction models can enhance risk stratification and stage-wise identification of CKD in HIV patients.
This makes it technically feasible to collect, process, and analyze patient data for research or clinical application.
223 Operational Feasibility Healthcare providers treating HIV patients are already trained in managing comorbidities.
Integrating kidney function monitoring into existing HIV care frameworks is achievable without requiring major infrastructure changes.
Multidisciplinary collaboration between nephrologists, infectious disease specialists, and data scientists can further strengthen operational feasibility 224.
Economic Feasibility Although advanced diagnostic tools and machine learning applications may involve initial costs, routine CKD screening (urine dipsticks, creatinine measurement) is cost-effective in the long term.
Early identification and management of CKD can reduce the financial burden associated with end- stage kidney disease, dialysis, and hospitalizations, making this approach economically justifiable 225 Social and Ethical Feasibility Patients with HIV often face stigma, which can affect healthcare access.
Designing CKD monitoring programs within existing HIV clinics ensures confidentiality and patient comfort.
Ethically, early detection and timely management of CKD uphold the principles of equity and improved quality of life for vulnerable populations A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 17 TJIT Department of MCA 2024-2025 23 Tools and Technologies Used 231 Python 38+ language Software and Python 38+ offers a practical, developer-friendly environment for building machine-learning pipelines that identify chronic kidney disease (CKD) stages in people living with HIV.
Using well-tested libraries like pandas and NumPy for data cleaning, scikit-learn or X G Boosting for model training, and matplotlib or Plotly for visualization, researchers can quickly iterate from raw clinical records to validated predictions.
Newer Python features such as type hints, data and classes for clean data models, and the walrus operator (:= for concise in-line assignments make preprocessing code easier to read and maintain, while strong package support for reproducibility (virtual environments, pip/Conda lock files) helps ensure results can be re-run across institutions.
When working with sensitive health data, Python's ecosystem also simplifies implementing privacy safeguards robust libraries enable secure data loading, stratified cross- validation to avoid leakage, and explainability tools (SHAP, LIME) to surface which clinical markers drive stage predictions.
Combining careful feature engineering eg, lab trends, eGFR calculations, comorbidity flags with model calibration and clinician-in-the-loop validation produces outputs that are not only accurate but also clinically interpretable.
In short, Python 38+ provides the tools and readability needed to translate HIV patient data into trustworthy,

actionable CKD stage assessments.

Key Features of Python 38+ are as follows ➢ Interpretation Python 38+ coding is executed by the interpreter at running time so there is no related compilations.
Such examples of other interpreted language include Perl and PHP.

➢ User Interactive Users can write and execute Python 38+ programs directly through the interactive promptings, making it stone for experimentations and learnings.

➢ Object-Oriented Programs Python supporting the OOP's which gives access to code to be organised into objects for better modularise and reusable contents.

➢ Beginner-Friendly Python is ideal for freshers allowing them to develop a diverse range of uses ranging from basic text processing to the internet development and gaming.
2311 History of Python 38+ Coming to the history of chronic kidney disease (CKD) stage identification in HIV-infected patients has evolved alongside advances in both medicine and data science.
Traditionally, physicians relied on clinical markers such as serum creatinine levels, glomerular filtration rate (GFR), and urine tests to determine kidney function.
However, HIV infection complicates this process, as antiretroviral therapy and viral progression can alter kidney health in ways not always detected by conventional methods.
Over the past decade, machine learning has emerged as a powerful tool to analyze large clinical datasets, identify hidden patterns, and improve early A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 18 TJIT Department of MCA 2024-2025 detection of CKD stages in HIV patients.
Using Python 38+ and its libraries (like scikit-learn, TensorFlow, and X G Boosting), researchers can now build predictive models that go beyond simple threshold values, providing more accurate and individualized risk assessments.
Looking ahead, the future of this field lies in integrating electronic health records, genomic data, and real- time monitoring with advanced machine learning models.
This will not only enhance stage identification but also support personalized treatment strategies, reduce complications, and ultimately improve the quality of life for people living with HIV.
231 Pandas and NumPy Constructed using Python language, In medical data analysis, especially when dealing with complex conditions like chronic kidney disease (CKD) in HIV-infected patients, efficient data handling and visualization are essential.
Pandas and NumPy serve as the backbone for this process, providing the foundation for data preparation and exploration.
Pandas offers powerful tools through its Data Frame structure, which allows researchers to manage patient information in a tabular format similar to spreadsheets.
This makes it easier to load, clean, and transform medical records, such as demographic details, laboratory test results, and clinical observations.
For instance, missing values in patient data can be identified and handled effectively using Pandas, ensuring that the dataset is consistent and reliable before it is passed on to machine learning models.
Alongside Pandas, NumPy enhances computational efficiency by enabling operations on large arrays of numerical data.
Since clinical datasets often contain thousands of rows and multiple variables NumPy's optimized functions allow calculations such as averages, standard deviations, and matrix operations to be performed quickly.
This reduces computational overhead and ensures smooth preprocessing when building predictive models for disease staging.
Another essential tool in this workflow is the heatmap in which is particularly valuable for exploratory data analysis.
A heatmap provides a color-coded visualization of the correlation between different features in the dataset.
In the context of CKD identification among HIV patients, it can be used to identify how laboratory markers such as creatinine levels, glomerular filtration rate (GFR), haemoglobin counts, and other clinical parameters are interrelated.
By observing the intensity of colours such as in the python colors in the heatmap, researchers can easily detect strong positive or negative correlations.

For example, a strong negative correlation between GFR and creatinine may reinforce the medical understanding that higher creatinine levels often indicate deteriorating kidney function.
Similarly, patterns linking HIV-related parameters with kidney health indicators can be uncovered, which may not be immediately visible through raw numbers.
This step helps narrow down the most influential features, allowing machine learning algorithms to focus on the variables that matter most for accurate staging of CKD.
Together, Pandas, NumPy, and heatmaps create a streamlined approach to medical data analysis.
Pandas organizes the information, NumPy accelerates the computations, and heatmaps provide intuitive insights through visualization.
This combination not only simplifies the A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 19 TJIT Department of MCA 2024-2025 preprocessing stage but also strengthens the foundation for building reliable predictive models.
Ultimately, these tools help transform complex medical datasets into actionable insights, enabling researchers to better understand the progression of chronic kidney disease in HIV-infected patients and improve decision-making in healthcare.
Table 1 Shows HTTP Methods SrNo Methods & Description 1 GET Transmits unencrypted data to the server most popular approach.
2 SEND Functions like GET but do not include a response body.
3 POST Data from HTML forms is sent to the Host by means of this technique.
The host does not cache information obtained via POST.
4 UPDATE The PUT method replaces all existing depictions of the intended resource with the uploaded content.
5 DELETE The DELETE method removes all present depiction of the designated resource by the URL.
A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 20 TJIT Department of MCA 2024-2025 24 System Hardware And Software Specifications 241 System Hardware Needed ➢ Processor Minimum i5 Processor.

➢ Storage 500 GB Storage or more.

➢ Monitor 14–17-inch Full HD OLED Display ➢ Input Devices Keyboard and optical Mouse (or Touchpad) ➢ RAM 8 GB RAM or higher than that 242 System Software Requirements ➢ (OS)Operating System Windows 10 / Ubuntu 2204 LTs ➢ Programming Language Python 38+ or later on ➢ Web Framework Stream lit (latest stabled versions) 3 (SRS) SPECIFICATION OF SOFTWARE REQUIREMENTS Specification of Software Requirements are the purpose of this project is to develop a machine learning–based system that can accurately identify and classify the stages of chronicA Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 21 TJIT Department of MCA 2024-2025 kidney stage disease (CKD) in patients who are also infected with HIVs.
Beginning detection and staging will assist healthcare providers in better treatment planning, risk assessment, and timely intervention, ultimately improving patient outcomes.

Why SRS is Important ➢ Detect the presence of CKD which clearly understands Helping the web developers to know exactly what needs to be built at this time.

➢ Classify the disease into appropriate stages (Stage 1 to Stage 5).

➢ Guiding Designs Provides a road mapping for system's designing and architectures.

➢ Provide predictive insights for clinicians.

➢ Project Planning is important Helps in estimating the types, amt, and resources used.
31 Users 311 The User Functions Coming to the design of the system focuses on offering a simple and efficient way for healthcare professionals and researchers to manage, analyse, and interpret patient data securely.
The platform is created to be user-friendly, ensuring that even users with minimal technical expertise can operate it smoothly.

Key user functionalities include ➢ Patient Data Management Authorized users can securely upload, update, and organize patient medical records, including test results and historical health data.

➢ Stage Prediction using ML Models Users can input patient parameters, and the system automatically predicts the stage of chronic kidney disease using machine learning algorithms.

➢ Search and Retrieval of Records Users can easily search for patient data, treatment history, or diagnostic results through a structured search interface.

➢ Access Control and role management Only authorized healthcare providers can access sensitive patient information, with different roles (eg, doctors, nurses, researchers) having specific access levels.

➢ Activity Monitoring Medical reports, lab results, and diagnostic charts can be safely uploaded and downloaded without risk of unauthorized access.

➢ Secure Data Upload & Download Users can safely upload files to the system and download them without risk of interception or unauthorized access.

➢ Visualization & Reporting Users can generate easy-to-understand visual reports and graphs showing patient health trends and disease progression.

➢ Multi-Platform Access The system can be accessed securely from multiple devices, ensuring flexibility for healthcare workers in hospitals or remote clinics.

➢ Notification and Alerts Users receive timely alrts regarding abnormal test values, disease progression, or urgent follow-up requirements.

 ➢ Data Backup and Recoveries Encrypted backups ensure that patient data can be restored in case of system failure or accidental deletion.

➢ User-Friendly Dashboard The interface is designed to be intuitive, enabling smooth navigation for both medical and non-technical staff.

This setup ensures that the data integrity and confidentiality while keeping the interface simple and intuitive.

312 Admin Functions The admin is in charge of overseeing user accounts and overseeing system operations.

Key admin functionalities include ➢ User Account & Role Management Admins can create, update, or remove user accounts and assign specific roles (eg, doctor, nurse, researcher) with corresponding access privileges.

➢ Data Access Control Administrators define and enforce access policies, ensuring only authorized personnel can view or modify sensitive patient data.

➢ System Monitoring & Audit Logs All user activities, including data uploads, predictions, and report generation, are tracked and available for auditing to maintain transparency and accountability.

➢ Model Training & Updates Admins can oversee the machine learning models, retrain them with new patient datasets, and update algorithms to improve prediction accuracy.

➢ Database Management Administrators manage patient databases, ensuring that records are properly stored, indexed, and protected from unauthorized access.

➢ Backup & Recovery Regular data backups can be scheduled by admins to safeguard against accidental loss, with recovery options available in case of system failure.

➢ Security & Compliance Admins are responsible for implementing encryption standards, password policies, and compliance with healthcare regulations (eg, HIPAA or local medical data laws).

➢ System Performance Monitoring Administrators can track the performance of servers, storage, and network usage to ensure smooth system operation.

➢ Notification & Alert Settings Admins configure alrts for critical events, such as failed login attempts, unusual system activity, or pending model updates.

➢ Multi-Device & Remote Access Management Admins control how and where the system can be accessed, allowing secure use across multiple devices while preventing unauthorized logins.

➢ Interface Customization Administrators can adjust dashboard views, reports, and system preferences to suit organizational needs.

 32 Functional Requirements Requirements The system is designed to assist healthcare professionals in diagnosing and monitoring chronic kidney disease (CKD) stages in HIV-infected patients using machine learning.

The following functional requirements define what the system should be able to do Patient Data Input and Management, Data Preprocessing and Validation,and CKD stage prediction, along with their specific capabilities.

321 Patient Data Input and Management ➢ The system should provide a secure and structured way for healthcare professionals to enter patient information such as demographic details, laboratory test results, and clinical history.

➢ It must also support importing existing data from hospital records or laboratory systems to reduce manual entry and ensure consistency across multiple sources.

322 Data Preprocessing and Validation ➢ Before the machine learning models can be applied, the system must clean and validate the data.

➢ In this includes handling missing values, removing inconsistencies, and standardizing formats so that the input is accurate and reliable it also allows marketers to be tailored campaigns for specific products or services based on the customer behaviours and their satisfaction.

➢ Automated checks and guided corrections should help users address common errors quickly.

323 CKD Stage Prediction ➢ The system must use trained machine learning algorithms to classify patients into different stages of CKD.
Along with the stage prediction, it should provide confidence scores or probability values to help healthcare workers assess the reliability of the result.
This ensures that clinical decisions are based on clear evidence.

➢ Prediction outcomes should be presented in an easy-to-understand format.
The system must generate visualizations such as graphs, charts, and summarized reports, making it easier for doctors to interpret disease progression.
Critical findings should be highlighted so that urgent cases receive immediate medical attention.

➢ Healthcare professionals should be able to search and retrieve patient records efficiently.
The system must include filters to sort information by patient ID, test type, CKD stage, or time frame.
This functionality ensures that doctors can quickly access the exact information they need during consultations.

33 Non-Functional Requirements 331 Requirements for Performances ➢ Definition The system must provide quick responses when processing patient data and generating CKD stage predictions.
Even with large datasets containing thousands of patient records, the system should maintain high performance without significant delays.
A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 24 TJIT Department of MCA 2024-2025 ➢ User’s Support Since healthcare workers rely on timely information, the machine learning models should be optimized to deliver results within seconds.

➢ Device Securities Even with large datasets containing thousands of patient records, the system should maintain high performance without significant delays.

332 Safety Requirements ➢ The system is essential in healthcare systems, as doctors and researchers need continuous access to patient records and predictions ➢ The system must be available with minimal downtime, and built-in fault tolerance should ensure that it continues to function correctly even in case of partial failures.

333 Security Requirements ➢ Because sensitive health information is being processed, the system must implement strong security protocols.
Patient data must be encrypted both during storage and transmission.

➢ Role-based access control should prevent unauthorized entry, and security audits must be regularly conducted to protect against data breaches.

334 Compliance with Medical Standards ➢ Reliability The system should validate inputs, handle errors gracefully, and display informative messages when issues occur it should continue functioning reliably without crashing.

➢ Usability The platform should have a simple, intuitive interface so that healthcare professionals with limited technical knowledge can use it without difficulty.
Navigation should be clear, and features like search, visualization, and reporting should be designed to reduce the learning curve.
User feedback mechanisms can further improve usability over time.

➢ Maintainability The system must be designed so that it is easy to update, debug, and extend.
Regular updates to machine learning models, security patches, and interface improvements should be applied without disrupting ongoing operations.
Clear documentation must also be provided to support future development and maintenance activities.

➢ Interoperability To integrate smoothly into healthcare environments, the system should be compatible with existing hospital management systems and laboratory databases.
This ensures that patient data can be imported and exported seamlessly, reducing duplication of work and improving efficiency A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 25 TJIT Department of MCA 2024-2025 4 SYSTEM DESIGN 41 SYSTEM ARCHITECTURE 411 chronic kidney disease (CKD) Dataset To identify and predict the stages of chronic kidney disease (CKD) in HIV-infected patients, a clinical dataset is required.
The dataset is carefully structured to include both medical and demographic information of patients, ensuring that the machine learning models can learn patterns and make accurate predictions.
Key Features of the Dataset A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 26 TJIT Department of MCA 2024-2025 ➢ Patient Demographics Age, gender, and relevant lifestyle details that may influence kidney health.

➢ Medical History Information on HIV infection status, duration of illness, and any ongoing treatments.

➢ Clinical Parameters Blood Tests Serum creatinine, haemoglobin, albumin, sodium, potassium, blood urea, and random blood glucose levels.
 Urine Tests Presence of proteins, pus cells, red blood cells, and specific gravity.
 Vital Signs Blood pressure and body mass index (BMI).

➢ HIV-related Indicators CD4 count, viral load, and ART (Antiretroviral Therapy) history, which are significant for assessing kidney complications in HIV patients.

➢ Disease Staging Labels Each record is tagged with the CKD stage (Stage 1 to Stage 5) or non- CKD, which acts as the target variable for model training.

➢ DatasetPurpose This dataset enables machine learning algorithms to analyze complex relationships between HIV infection, clinical measurements, and kidney disease progression.
By doing so, it helps in early detection, stage classification, and risk prediction.
Data Security and Privacy All patient records are anonymized before inclusion to ensure confidentiality and ethical handling of sensitive medical information.

➢ Data Security and Privacy All patient records are anonymized before inclusion to ensure confidentiality and ethical handling of sensitive medical information.

412 Preprocessing and Feature Preparation ➢ Data Cleaning Missing values are filled, duplicates removed, and outliers corrected.

➢ Feature Encoding Categorical attributes are converted into numerical values.

➢ Feature Scaling All features are normalized or standardized to a common scale.

➢ Feature Selection Only clinically and statistically relevant features are retained.

➢ Data Splitting Dataset is divided into training, validation, and testing sets.

➢ Balancing the Dataset Class imbalance is handled using oversampling or undersampling.

➢ Feature Engineering New meaningful features like eGFR are derived from existing data.
413 (SVM) Model Architecture Input Features Patient details such as age, lab results, HIV status, and kidney function values are taken as input to help the model learn disease patterns.
A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 27 TJIT Department of MCA 2024-2025 Data Preprocessing Missing values are filled, categorical values are converted into numbers, and features are scaled so that the model treats all data fairly.
 Class Balancing Since some CKD stages may have fewer patients, balancing methods like class weights or oversampling are used to prevent bias.
 Feature Selection Only the most important clinical features are chosen to make the model efficient and reduce noise.

 SVM Classifier A Support Vector Machine is used, which separates patient data into different CKD stages using kernels (linear or RBF).
 Hyperparameter Tuning Parameters like C and gamma are optimized through cross- validation to improve accuracy and avoid overfitting.
 Model Training & Validation The dataset is split into folds (eg, 5 or 10) to train and test the model fairly, ensuring reliable results.
 Evaluation Metrics The model is judged using recall, F1-score, ROC curves, and confusion matrices to check clinical usefulness.
 Interpretability Feature importance and tools like SHAP/LIME are used to explain predictions, making results understandable for doctors.
 Deployment The final pipeline is saved and can be used to predict CKD stage from new patient data in real time.
 Limitations SVM may overfit with small datasets or noisy features, so regular updates and clinical validation are required.

314 Performance Analysis and Visualization ➢ Accuracy Evaluation The system measures how precisely the ML model predicts CKD stages in HIV patients, ensuring reliable diagnostic support.

➢ Confusion Matrix Insights It visually represents true positives, false positives, and errors, helping doctors understand where the model performs best.

➢ ROC and AUC Curves These charts highlight the system's ability to differentiate between disease stages, giving a clear picture of prediction strength.

➢ Precision and Recall Check By analyzing these metrics, users can see how well the system balances correct detection versus missed cases.

➢ Trend Visualization Patient data and disease progression are shown through graphs and charts, making complex health patterns easy to interpret.

➢ Comparative Model Analysis Different ML models can be compared visually, so users can identify which provides the most accurate results.

➢ Real-Time Dashboards Interactive dashboards display predictions and performance updates instantly, supporting quick medical decisions.

A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 28 TJIT Department of MCA 2024-2025 415 System Perspective A The system is designed as an intelligent healthcare support platform that integrates patient data with machine learning models to assist doctors in identifying the stage of chronic kidney disease (CKD) in HIV-infected patients.
It acts as a decision-support tool, not as a replacement for medical professionals, helping to improve accuracy and reduce diagnostic delays.
From a system perspective, the framework consists of three main layers Data Collection Layer – This layer gathers patient information such as demographic details, medical history, laboratory test results (eg, creatinine levels, blood pressure, CD4 counts), and lifestyle factors.
The data is securely stored and pre-processed to ensure accuracy and consistency.
Machine Learning Layer – In this stage, the system applies advanced ML algorithms to analyze the data.
The models are trained to detect patterns and predict the CKD stage, taking into account the complications caused by HIV infection.
The algorithms are built to continuously improve as more patient records are added.
User Interaction Layer – This is the interface that healthcare professionals and researchers interact with.
It provides an easy-to-use dashboard where users can input patient details, view stage predictions, generate reports, and track disease progression over time.
The design emphasizes simplicity so that even users with limited technical expertise can navigate it without difficulty.
The system also integrates security measures such as role-based access, encrypted storage, and regular activity logging to protect sensitive patient information.
In addition, features like data visualization, automated alrts for critical cases, and multi-device support make it practical for real-world healthcare environments.

Overall, this system perspective ensures that the platform is not only technically sound but also reliable, secure, and user-friendly, bridging the gap between medical expertise and machine learning technology for better patient outcomes.
42 Context Diagram Explanation 421 DATA FLOW DIAGRAM (Level 0) The flowchart illustrates the step-by-step process of Chronic Kidney Disease (CKD) stage identification in HIV-infected patients using Machine Learning.
The process begins with the collection of patient data, including laboratory results, medical history, and HIV-related information.
This raw data is then subjected to data preprocessing, where missing values are handled, data is normalized, and noise is removed to ensure accuracy.
Next, the system performs feature selection, identifying the most relevant clinical indicators such as serum creatinine, hemoglobin levels, blood pressure, and other important biomarkers.
These selected features are then used to train a machine learning model using algorithms like Decision Trees, Support Vector Machines, or Neural Networks.
Once trained, the model can perform stage identification, A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 29 TJIT Department of MCA 2024-2025 predicting whether the patient falls into CKD Stage 1 through Stage To ensure reliability, the system undergoes model evaluation, where accuracy and performance are validated against real test cases.
Finally, the clinical support output is generated, providing doctors with valuable insights to assist in diagnosis and treatment planning.
The process concludes with secure delivery of results, making the entire workflow efficient, reliable, and supportive for healthcare professionals.
422 Diagram START PATIENT DATA INPUT FEATURE SELECTION ML MODEL TRAINING STAGE IDENTIFICATION END MODEL EVALUATION CLINICAL SUPPORT OUTPUT A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 30 TJIT Department of MCA 2024-2025 423 How it works In the Level 0 DFD for the system Data Collection o The Patient information such as age, gender, HIV status, blood pressure, blood sugar, creatinine levels, protein in urine, and other lab values is collected from hospital records or diagnostic labs.
Data Preprocessing o Since medical data often contains missing values or inconsistencies, the system cleans and standardizes it.
For example, missing lab results may be handled, and values are normalized so that the ML model can process them effectively.
Feature Selection o The system identifies the most important health indicators (features) that contribute to CKD progression, such as glomerular filtration rate (GFR), blood urea, hemoglobin levels, and albumin.
This reduces noise and improves prediction accuracy.
Model Training o Machine learning models (such as Decision Trees, Random Forest, Support Vector Machines, or Neural Networks) are trained on historical patient data where the CKD stage is already known.
The system “learns” the patterns that differentiate between early-stage CKD, moderate CKD, and advanced stages.
Prediction Process o When a new patient’s data is entered, the trained ML model analyzes the input and predicts the current CKD stage.
This helps doctors understand whether the patient is at risk, in the early stages, or already in an advanced stage of kidney disease.
Result Interpretation & Visualization o The system provides outputs in an easy-to-understand format, often with charts or graphs.
For example, it may show a trend of kidney function over time or highlight abnormal values that need attention.
Decision Support for Doctors o Doctors can use these predictions to make quicker, evidence-based decisions about treatment plans, such as medication adjustments, dialysis requirements, or closer monitoring for high-risk patientsA Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 31 TJIT Department of MCA 2024-2025 5DETAILED DESIGN 51 USE CASE DIAGRAM A Use Case Diagram shows the interactions between users (actors) and the system.
It helps visualize the main tasks the system performs and who performs them, making it easier for developers

and healthcare professionals to understand the system's functionality.
Actors Healthcare Provider / Doctor – interacts with the system to input patient data and receive predictions.
Administrator – manages user accounts, data access permissions, and system settings.
Patient (optional) – provides health records and lab results (directly or through the hospital system).
Use Cases Upload Patient Data o Doctors or healthcare staff upload patient medical history, lab test results, and clinical records in the system.
Preprocess Data o The system cleans, normalizes, and organizes patient data for analysis.
Feature Selection & Extraction o The system identifies key indicators from the data (creatinine, haemoglobin, blood pressure, CD4 count, etc) for machine learning analysis.
Train Machine Learning Model o The administrator or system trains the ML model (eg, SVM) using historical patient data to recognize patterns for CKD stage prediction.
Predict CKD Stage o Doctors input new patient data, and the system predicts the CKD stage (Stage 1–5) using the trained model.
Test Model Accuracy o The system evaluates predictions on test data to ensure reliability and accuracy of the ML model.
Generate Report / Dashboard A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 32 TJIT Department of MCA 2024-2025 o The system displays predicted CKD stage along with visual reports for easy interpretation by healthcare providers.
Manage Users & Permissions o Administrators control access levels, assign roles, and ensure that only authorized personnel can access sensitive patient data.
Purpose ➢ The Use Case Diagram clarifies how each actor interacts with the system.
➢ It ensures that the responsibilities of doctors, administrators, and the system are clearly defined.
➢ Helps in planning and designing the system for smooth operation and secure handling of patient data.
511 DFD Level 1 A Level 1 Data Flow Diagram (DFD) gives a more detailed view of the system compared to Level 0.
While the Level 0 diagram represents the system as a single large process, the Level 1 diagram breaks that main process into smaller, well-defined sub-processes.
This helps in understanding how data flows step by step within the system and how different modules work together.
In Level 1 DFD for CKD Stage Identification in HIV Patients Decomposition of Processes o The overall system process is divided into smaller sub-processes such as Patient data collection, Data preprocessing, Feature extraction, ML prediction and Report.
o Each sub-process performs a unique task that contributes to the final prediction of the CKD stage.
Detailed Data Flows o Data flows are shown between sub-processes, external entities, and data storage units.
o For example, patient medical records flow into the preprocessing module, transformed data moves to the ML model, and prediction results are sent back to healthcare providers.
o This makes it clear what information is used, how it is processed, and where it is directed at each stage.
External Entities and Data Stores o External entities such as Doctors, Lab staffs and patients interact with the system by providing input data or receiving outputs.
o Data stores include Patient Medical Database, and Trained ML Models, which support the processes by holding and retrieving essential information.
Purpose and Benefits A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 33 TJIT Department of MCA 2024-2025 o The Level 1 DFD helps stakeholders such as developers, medical researchers, and hospital administrators gain a clear understanding of how the system functions internally without overwhelming technical details.
o It is highly useful for planning, communication, and ensuring that every step in the system is accounted for before moving into coding or system deployment.
511 Diagram Fig Shows DFD Level 1 511 How it works Input Data (CSV Files) o Patient medical records, lab test results, and clinical history are collected in csv format.
o These files contain important parameters such as creatinine levels, haemoglobin, blood pressure, and CD4 counts.
Input files Preprocessing Training the dataset SVM Feature Extraction Prediction Testing Data Result of the

CKD In HIV patients A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 34 TJIT Department of MCA 2024-2025 Data Preprocessing o Raw data is cleaned to handle missing values, outliers, or inconsistent entries.
o Data normalization and transformation are applied to make it suitable for machine learning analysis.
Training Dataset o The pre-processed and feature-selected dataset is fed into the machine learning model (eg, SVM – Support Vector Machine).
o The model learns patterns in the data to distinguish between different stages of CKD.
SVM Feature Extraction o Relevant features from the patient dataset are selected that influence CKD stage prediction.
o Examples include kidney function markers, blood test parameters, and HIV-related indicators.
o This step converts unprocessed Convert picture data into actionable insights that the classifier can use.
Prediction / Classification o Once trained, the system can predict the CKD stage of new patients using the ML model.
o Input features of a patient are processed, and the model outputs the predicted CKD stage to predict whether the stage is in stage 1, stage 2, stage 3, stage 3A etc.
Testing Data o Separate test datasets are used to validate the model's accuracy and reliability.
o The system evaluates performance metrics like precision, recall, and overall accuracy.
Result of the Facial Expression o Predicted CKD stage is displayed in a user-friendly report or dashboard accuracy or confidence scores.
o Healthcare providers can use these results to make informed decisions about patient care and treatment plans.
512 Diagram A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 35 TJIT Department of MCA 2024-2025 Fig Shows Use case diagram 512 How it works A use case diagram illustrates the interaction between different users and the system, showing how each actor engages with the processes.
In the context of CKD stage identification in HIV-infected patients using machine learning, the diagram highlights the roles of the doctor, the patient, and the ML system.
The doctor or healthcare professional is the primary actor who interacts directly with the system by entering patient information such as laboratory results, HIV- related markers like CD4 count and viral load, and kidney health indicators including creatinine and proteinuria levels.
The patient, although not directly interacting with the system, plays an indirect role by providing the medical data needed for input.
Once the data is entered, the ML system takes over and preprocesses the information to ensure it is clean and structured for analysis.
After this step, the prediction model is executed, where the system applies trained algorithms to evaluate the patient's health status.
The output of this analysis is the identification of the specific CKD stage, ranging from Stage 1 to Stage 5, based on clinical patterns and risk markers.
Following this, the system generates a clear and structured report that provides the doctor with both the stage classification and additional insights on disease progression.
The doctor then uses this information to make informed clinical decisions, such as adjusting medications, recommending lifestyle changes, or referring the patient for specialized care.
In essence, the use case diagram captures the flow of interaction where the doctor communicates with the ML system to process patient information, obtain CKD stage predictions, and apply the User Files input Data Preprocessing ML Training Prediction A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 36 TJIT Department of MCA 2024-2025 results to improve the quality of care, while the patient benefits indirectly through more accurate and personalized treatment.
52 Sequence diagrams A sequence diagram shows how different parts of the system interact step by step over time.
In the context of predicting Chronic Kidney Disease (CKD) stages in HIV-infected patients using ML, the diagram highlights the flow of activities between the user (doctor or researcher), the system (ML model and database), and the output (predicted stage and treatment guidance).
User Input 6 7 The process begins when a healthcare professional or researcher enters patient details into the system.

These details include clinical information such as age, blood pressure, viral load, CD4 count, serum creatinine, proteinuria, and other relevant lab values.
8 9 10 11 Data Preprocessing 12 13 Once the data is submitted, the system checks for missing or inconsistent values.
14 15 Data is cleaned, normalized, and structured in a way that the machine learning model can understand.
16 Model Interaction 17 The pre-processed data is then sent to the ML model.
18 The model, which has been trained on historical patient datasets, analyzes the input and compares it with learned patterns.
19 20 21 22 Prediction of CKD Stage 23 24 Based on the trained algorithms, the model classifies the patient's kidney health into a specific CKD stage (eg, Stage 1 to Stage 5).
25 26 This classification is done by analyzing kidney function markers such as eGFR and protein levels, along with HIV-related factors.
27 28 29 30 Results Delivery 31 32 The predicted CKD stage is sent back to the user interface.
33 34 The system may also provide additional insights like progression risk, suggested monitoring frequency, or supportive treatment guidelines.
35 36 37 38 User Feedback/Decision 39 A Lightweight Convolutional Neural Network for Real-Time Facial Expression Detection 37 TJIT Department of MCA 2024-2025 40 Finally, the doctor or healthcare professional reviews the results.
41 42 Based on the prediction, they decide on further clinical actions, such as adjusting medication, increasing follow-up visits, or referring the patient for specialized care.