

The Current and Future of Machine Learning and Deep Learning in the Treatment of Autoimmune Diseases

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Abstract. Autoimmune illnesses pose formidable diagnostic and prognostic obstacles due to the wide range of symptoms they cause and the immune system's tendency to malfunction, which in turn causes the creation of autoantibodies. Although early diagnosis and personalized treatment are of the utmost importance, traditional approaches sometimes lack predictive power. Through the analysis of massive datasets and the creation of sophisticated diagnostic and prediction tools, machine learning (ML) presents a promising approach to addressing these challenges. protocols for autoimmune diseases affecting several organs and systems (e.g., rheumatoid arthritis, SLE, lupus erythematosus). (The autoimmune thyroid disease, gastrointestinal disorders, skin diseases, and type 1 diabetes mellitus are all examples). The growing promise of machine learning algorithms for issue predicting, therapeutic response evaluation, and early disease detection is highlighted by our work. To go a step further, we look at how ongoing research and the addition of more varied and extensive datasets might improve these models' accuracy and dependability. This will enable healthcare providers to detect autoimmune diseases at an early stage and guide the creation of efficient treatment strategies.

Keywords: autoimmune conditions, bowel inflammation disorders, machine learning, rheumatoid arthritis, systemic lupus erythematosus, diabetes mellitus type1

1 Introduction

Autoimmune diseases occur when the immune system attacks the body's own tissues, producing autoantibodies and autoreactive immune cells that cause organ damage and diverse clinical symptoms. Nearly 20% of cases have a hereditary link, and these disorders are generally classified into systemic conditions, such as systemic lupus erythematosus (SLE), and organ-specific diseases like autoimmune thyroid disorders. Their complex and heterogeneous nature makes early diagnosis and personalized treatment difficult, as traditional methods often lack predictive accuracy. In recent years, artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has shown great promise in addressing these challenges by analysing large clinical, genetic, and imaging datasets to improve diagnosis, predict disease progression, and support individualized therapies.

2 Systemic Lupus Erythematosus (SLE)

The annual incidence of SLE, a chronic autoimmune illness that damages and inflames the body's own cells and tissues, ranges from 1.5 to 11 cases per 100,000 persons worldwide. It is more common in women and certain ethnic groups. Immunological biomarkers and other diagnostic methods for systemic lupus erythematosus have grown in importance over the years. According to the current categorization criteria, which were revised in 2019 by the European League Against Rheumatism (EULAR) and the American College of Rheumatology (ACR), positive antinuclear antibodies (ANA) are one of the clinical signs that must be present. Some of these conditions include immunological abnormalities including antibodies against phospholipids and complement proteins as well as specific antibodies associated with systemic lupus erythematosus (SLE). Other conditions include problems with the constitution, blood, neurology, psychiatry, skin, bones, and kidneys. These criteria have a specificity of 93.4% and a sensitivity of 96.1%, making them very useful for diagnosing SLE. Prognostic models that use machine learning have the ability to foretell the course of a disease and the likelihood of its possible outcomes, such as the involvement of the kidneys or the incidence of cardiovascular events. Fig 1 shows Systemic Lupus Erythematosus (SLE) Affected Organs and Symptoms.

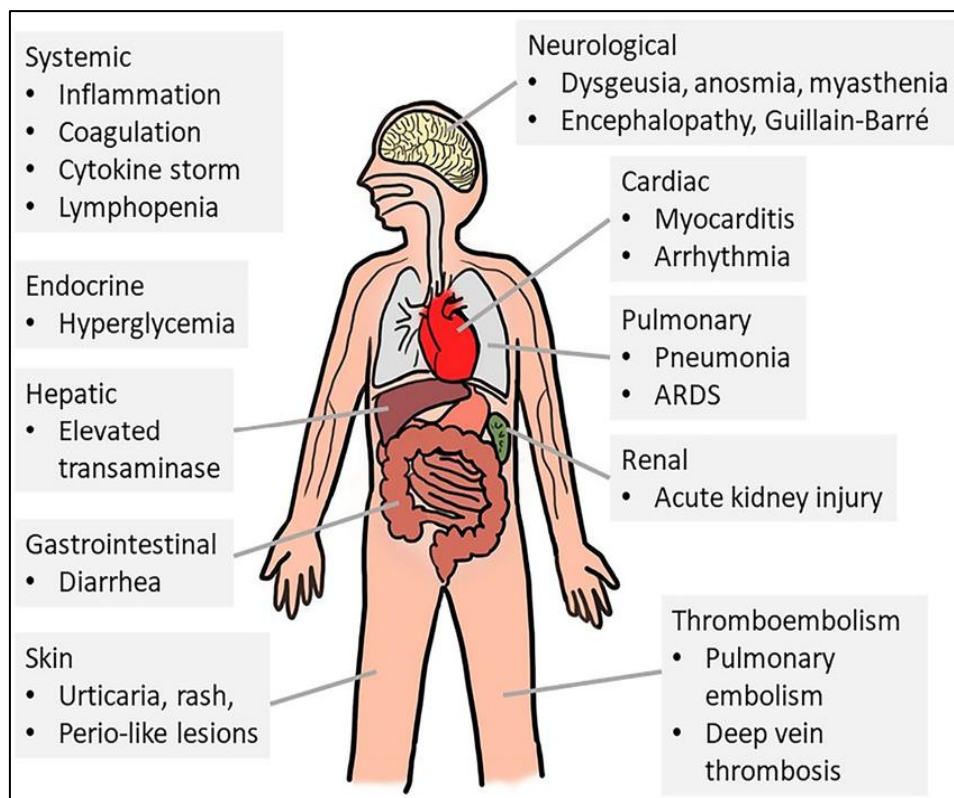


Fig. 1. Systemic Lupus Erythematosus (SLE) Affected Organs and Symptoms.[22]

The ML algorithms have been used therapeutically to evaluate the efficacy of treatment, predict response to medication, and optimize management strategies. Patients with SLE may be able to receive more tailored care and fewer “try and see” approaches to treatment through integration of ML approaches analysing clinical and immunological data to identify patterns that predict response to a specific medication [17]. Future application in the setting of SLE, ML may one day transform the diagnosis and treatment of this complex autoimmune disease. Better, more personalized care is within sight because of advances in early detection, forecasting of prognosis, and optimization of therapy. Immunologic markers (e.g., ANA positivity), in combination with other clinical symptoms of disease such as hematologic, neuropsychiatric, and musculoskeletal symptoms, will be used to build the 2019 EULAR/ACR guidelines.

3 Literature Review

Autoimmune Diseases and Clinical Challenges

Autoimmune diseases are characterized by the immune system mistakenly attacking the body’s own tissues, leading to chronic inflammation and organ damage. Wang et al. (2015) [1] provided a comprehensive update on the spectrum of autoimmune diseases, highlighting their complex pathogenesis and the challenges they pose for diagnosis and treatment. Wahren-Herlenius and Dörner (2013) [2] further explained the immunopathogenic mechanisms underlying systemic autoimmune conditions, emphasizing the interplay of genetic and environmental factors that complicate diagnosis and prognosis.

Advances in Immunotherapy and Cellular Approaches

Recent years have seen novel treatment approaches alongside computational advancements. Schett, Mackensen, and Mougiakakos (2023) [3] discussed the potential of CAR T-cell therapy as a revolutionary intervention in autoimmune diseases, indicating a shift toward targeted cellular immunotherapies. These biological advances complement computational tools by providing new clinical data streams for machine learning (ML) models.

The Role of Artificial Intelligence in Broader Medical Contexts

Machine learning and deep learning have been widely explored in diverse medical domains. Ghavidel and Pazos (2025) [4] systematically reviewed ML applications for breast cancer prediction, emphasizing challenges such as class imbalance and model interpretability—issues also relevant to autoimmune disease modeling. Similarly, Wieneke and Voigt (2023) [5] demonstrated how AI principles have been applied in cardiovascular medicine, offering insights into diagnostic and therapeutic strategies translatable to autoimmune contexts. Handelman et al. (2018) [8] projected the transformative role of AI in predictive healthcare through their “eDoctor” perspective, underscoring the capacity of ML to augment clinical reasoning.

Machine Learning in Systemic Lupus Erythematosus (SLE)

SLE has been a primary focus for ML research given its heterogeneous manifestations. Barber et al. (2021) [10] described the global epidemiology of SLE, which motivates the need for computational tools to handle complex datasets. Zhou et al. (2022) [11] conducted a systematic

review and meta-analysis, concluding that ML-based diagnostic tools improve accuracy in distinguishing SLE from other conditions. Munguía-Realpozo et al. (2023) [12] evaluated reporting standards in ML prediction models for SLE and highlighted the importance of adhering to frameworks such as TRIPOD (Collins et al., 2015) [13] to ensure reproducibility and clinical applicability.

On the biomarker discovery side, Huang et al. (2009) [14] applied proteomics and decision tree models to differentiate SLE patients, while Li et al. (2022) [15] combined proteomics with single-cell RNA sequencing to identify diagnostic and exacerbation biomarkers. Clinical data integration has also been studied extensively: Turner et al. (2017) [16] used natural language processing methods for lupus phenotyping, Jorge et al. (2019) [17] validated ML algorithms for patient identification in electronic health records, and Barnado et al. (2022) [18] extended ML applications to maternal outcomes in SLE. Murray et al. (2019) [19] further improved disease detection through flexible labeling methods, showing the adaptability of ML to noisy datasets.

Other Autoimmune Diseases and ML Applications

Research has extended beyond SLE to other autoimmune conditions. Danieli et al. (2022, 2023) [6][7] used ML to predict responses to immunoglobulin therapy and to evaluate treatment outcomes in inflammatory myopathies, demonstrating the potential for precision medicine. Chung et al. (2021) [20] explored ML approaches for the genomic prediction of rheumatoid arthritis (RA) and SLE, highlighting the shared computational frameworks across diseases. Rao and Raghuram (2020) [9] and Ghasemi et al. (2017) [21] provided essential clinical perspectives on SLE and multiple sclerosis (MS), respectively, offering disease-specific knowledge that enriches the computational modeling landscape.

Emerging Directions and Future Prospects

The integration of clinical, proteomic, genomic, and imaging data represents a significant opportunity for ML in autoimmune diseases. Li et al. (2022) [15] and Chung et al. (2021) [20] demonstrated that multi-omics approaches improve diagnostic accuracy and disease prediction. Looking forward, these methods may evolve into fully personalized medicine frameworks, where ML models not only diagnose but also optimize treatment strategies in real time.

Table 1. ML Studies on SLE Diagnosis.

Author	Aims	Data Input	Patient	Methodology	Result
Huang et al. [14]	Identify serum biomarkers and build diagnostic model	Serum proteomics	232	Boosting Decision Tree	Differentiated SLE vs. other autoimmune diseases (accuracy ~78–90%).
Turner et al. [16]	Compare text classifiers vs. Word2Vec	EHR notes	662	ANN, SVM, RF	RF (CUIs) 95.25% accuracy; shallow NN (CUIs) 92.1%.

Jorge et al. [17]	for SLE phenotyping Identify SLE patients in EHR	EHR data	300	ANN, RF	RF with CUIs 95.25%, SNN with CUIs 92.1%.
Murray et al. [19]	Retrieve SLE patients using noisy labels	EHR data	300	Logistic Regression	Combined structured + text data (AUC 0.97).
Barnado et al. [18]	Detect SLE births	EHR data	4,708	RF, XGBoost	Higher accuracy in African American women.
Li et al. [15]	Biomarker discovery for diagnosis and exacerbation	PBMC + scRNA-seq data	396	Random Forest	6-protein set (AUC 0.7–0.8); 9-protein set for flare-up (AUC 0.9).
Chung et al. [20]	Genomic-based early diagnosis of SLE	Genomic data	150+	XGBoost, Random Forest	Achieved strong sensitivity & specificity for genomic prediction.
Zhou et al. [11]	Systematic review and meta-analysis of ML for SLE diagnosis	Multi-source ML studies	N/A	Review & meta-analysis	Identified diagnostic accuracy trends across ML methods.
Mungui a-Realpoz o et al. [12]	Evaluate reporting standards (TRIPOD) in SLE ML prediction models	Clinical ML models	N/A	Systematic review	Highlighted reporting gaps and emphasized TRIPOD compliance in ML studies.
Rao & Raghuram [9]; Barber et al. [10]	Provide clinical/epidemiological background on SLE	Literature review	N/A	Review articles	Positioned SLE as a global autoimmune challenge, motivating ML applications.

4 Highlights

Several important predictors of hospitalization in SLE patients have been identified. These levels included C3 levels, anti-dsDNA levels, blood cell counts, inflammatory indices, and albumin.

- **Machine Learning Risk Prediction:** A number of machine learning models have been taken to predict potential risks for SLE patients, including thyroid disorder, cardiovascular disease, etc, and pregnant outcomes.

- **ML ABOUT RESPONSE TO THERAPY:** The use of machine learning (ML) models to predict therapeutic response in patients with SLE may lead to patient-tailored medicine.

4.1 Rheumatoid Arthritis (RA) -Diagnosis Rheumatoid arthritis (RA)

Impact of Rheumatoid Arthritis (RA) on Diagnosis The immune system of the body reacts abnormally in an inflammatory disorder termed as rheumatoid arthritis (RA) that is responsible for damaging joints and other parts of the body. Both genetic, immunologic, and environmental factors impact the development of RA, but remain poorly defined. Artificial intelligence (AI) may be used to improve doctors' ability to diagnose RA and determine individuals at risk for developing the disease. An early diagnosis is imperative in preventing permanent joint damage. The study by Arleevskaya et al. (2016) [23], explains that rheumatoid arthritis (RA) may arise when chronic or repeated infections by microorganisms and viruses provoke abnormal immune responses, triggering autoimmunity in genetically susceptible individuals. Fig 2 shows Viral Infection and Autoimmunity Process.

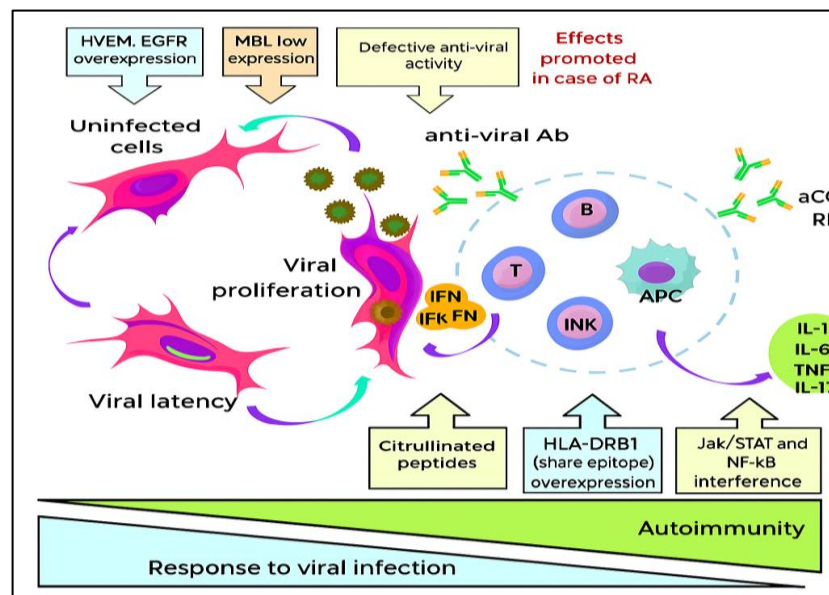


Fig. 2. Viral Infection and Autoimmunity Process [23].

A few studies applied machine learning (ML) strategies to anticipate the development of the disease and to diagnose early RA. The same was found when they found important markers in RA patients. (2016). The application of ML to identify cytokines as early predictors has also been reported in several studies. Additionally, CNN-based approaches have demonstrated the potential for classification of RA in image analysis based on clinical data and x-ray images. More research is necessary to improve and tailor these AI-driven diagnostic tools, as there remain barriers to the implementation of these models across diverse populations, despite recent advances.

5 Key Findings

- ML models (e.g., random forest and support vector machines) have been enhancing the early detection of RA, based on an analysis of clinical, genomic, and proteomic data.
- The search for new biomarkers is influenced by the low positive predictive value of the current biomarkers (CRP and ACPAs) despite being very useful.
- RA lodgement of algorithm framework based on clinical and histological information now has started using artificial intelligence frameworks such as in convolutional neural network (CNNs).

There is a small body of literature that will be discussed in the following table 2 and that highlights the state-of-the-art of relevant ML-related research around the diagnosis of RA. It covers it all from what the study set out to achieve, where the data came from, the count of patients, ML models, and key findings.

Table 2. Summary of Machine Learning-Based RA Diagnosis Studies.

Author	Aims	Data Input	Patient	Methodology	Result
Wang et al. [1]	Provide a comprehensive overview of autoimmune diseases including RA Review ML applications in autoimmune disease diagnosis (including RA methodology)	Literature review	N/A	Comparative analysis	Positioned RA as a key autoimmune disease, highlighting diagnostic challenges and background for ML applications.
Zhou et al. [11]	Develop genomic prediction models for RA and SLE	EHR, biomarkers, genomic data	N/A	Systematic review, meta-analysis	Identified key ML approaches (RF, decision trees, SVM, genomic models) applicable to RA diagnosis.
Chung et al. [20]		Genomic data	200+	XGBoost, Random Forest	Achieved strong sensitivity & specificity in early genomic-based RA diagnosis.

6 Key Insights

Machine learning models which are used for early diagnosis of RA, prediction of disease progression, and identification of biomarkers include, Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Networks (CNN).

The role of new biomarkers for diagnosing RA appears to be better than that of the conventional methods in a number of researches. In actual settings, the accuracy is high (up to 94%) by using both clinical and EHR-related data for RA diagnosis.

Autoimmune thyroid disorders:

The use of machine learning (ML) as a powerful tool in autoimmune thyroid diseases such as Graves' disease and Hashimoto's thyroiditis has advanced the development of diagnosis, prognosis and treatment prediction. Fig 3 shows Immunopathogenic Mechanisms Underlying Systemic Lupus Erythematosus.

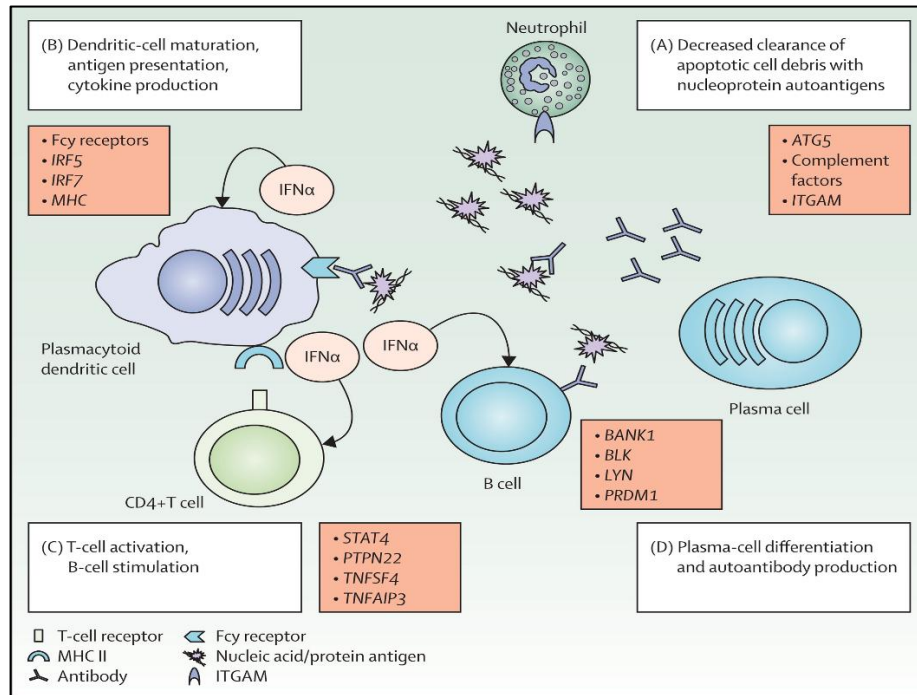


Fig. 3. Immunopathogenic Mechanisms Underlying Systemic Lupus Erythematosus.[2]

7 Graves' Ophthalmopathy

- The problem of prejudice. By combining laser-induced breakdown spectroscopy (LIBS) with k-nearest neighbour and generalised regression neural network models, a 2021 study details the successful identification of Graves' ophthalmopathy with an accuracy of above 95%.
- Different research from 2021 used AI to forecast how well glucocorticoid treatment would work for individuals suffering from active Graves' ophthalmopathy. Multivariate logistic regression was used to evaluate ocular morphological changes in order to tailor therapy.
- Biomarkers: Artificial intelligence (AI) prompted researchers to examine DNA methylation for possible indicators of Graves' ophthalmopathy. Study participants' immune cell infiltration patterns were associated with illness, and S100A11 and NKD2 were shown to be diagnostic indicators.

8 Prediction Model

- Using AI-based scoring models like SMSGOP and SMGOP, the course of Graves' ophthalmopathy may be predicted. The fact that these assessments are grounded in clinical data makes them valuable for therapeutic decision-making.
- XGBoost primarily utilizes TSI and LDL levels to determine the responsiveness of persons with thyroid eye illness to steroid therapy.

9 Prognostic Insights

- Using full blood count and biochemical data, a study from 2021 utilized machine learning to predict when Graves' disease and thyrotoxicosis will manifest. Serum creatinine and cholesterol levels were shown to be key prognostic markers.
- Differential Diagnosis: The causes of thyrotoxicosis were identified using ML, more especially random forest, which allowed for faster diagnosis and therapy choices.

10 Other Applications

- Thyrotoxic Atrial Fibrillation (TAF): The causes of thyrotoxicosis were identified using ML, more especially random forest, which allowed for faster diagnosis and therapy choices.
- Post-Therapy Hypothyroidism: Early management for Graves' illness might be facilitated in 2022 thanks to ML models that predicted hypothyroidism after radioiodine treatment.
- ML offers important predictive tools in autoimmune thyroid disorders, improves diagnostic precision, and personalises therapy. Table 3 shows Application of ML for Graves’ disease.

Table 3. Application of ML for Graves’ disease.

Author	Aims	Data Input	Patient	Methodology	Result
Wang et al. [1]	Provide a comprehensive overview of autoimmune diseases (including thyroid disorders)	Literature review	N/A	Comparative analysis	Identified Graves’ disease as a key autoimmune thyroid disorder and outlined diagnostic challenges relevant for ML.
Wahren-Herlenius & Dörner [2]	Explain immunopathogenic mechanisms of systemic	Immunopathogenic data, literature	N/A	Pathophysiological analysis	Described autoimmune pathways in thyroid disorders,

autoimmune
diseases

providing
background
for ML-
based
diagnostic
and
therapeutic
approaches
in Graves'
disease.

11 Cutaneous Autoimmune Disorders

- White spots on the skin caused by the loss of melanocytes is known as Vitiligo, and it is a common autoimmune skin condition. About 1% to 2% of the population is impacted by it, and it has a major impact on patients' mental health.
- Artificial intelligence applications for vitiligo seek to evaluate the severity of the condition, find biomarkers, and provide new methods of therapy.
- A hybrid AI model that detects and quantifies the severity of vitiligo lesions was produced by Chinese research using deep learning. With a sensitivity of 92.91%, YOLO v3 was able to identify lesions in two sets of 3,982 images. Dermatologists and the model reached a consensus when assessing size disparities and pigmentation. Fig 4 shows Psoriasis Pathogenesis Mechanism.
- Rock Creek Pharmaceuticals' Exhibit 99.1 presents the company's strategic focus on anti-inflammatory drug development and its preclinical and clinical data supporting the mechanism of action [24].
- The document also emphasizes the company's expectations, assumptions, and risks associated with its development plans via "forward-looking statements"

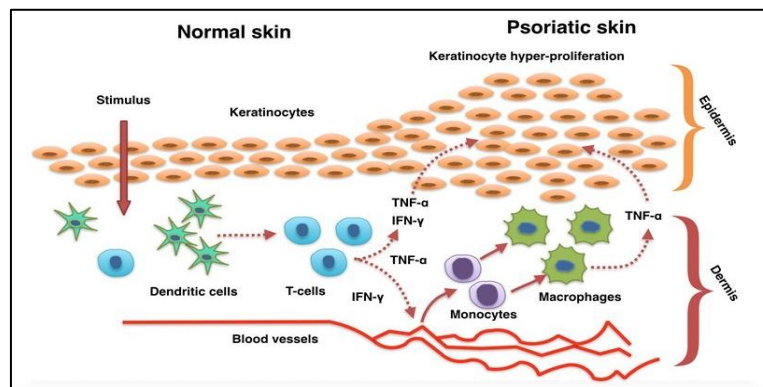


Fig. 4. Psoriasis Pathogenesis Mechanism. [24]

12 Alopecia

Alopecia areata, an autoimmune disease that doesn't scar the skin, strikes some 2 percent of the population, making hair fall out in clumps. Serious mental health issues, like anxiety and

depression, could also result. AI was used in alopecia research mainly for early assessment, severity estimation and therapeutic planning.

A computer imaging technique was applied to the measurement of alopecia severity and obtained 91% accuracy when classifying subjects with artificial neural networks. A new method as an alternative for self-diagnosis of scalp conditions was proposed and measures the progression of hair loss by understanding acquired variables, namely the thickness and follicle count of hairs with a microscope and smartphone. In another study, a classification system separating hair samples from healthy and alopecia subjects achieved 91.4 % accuracy using the support vector machines. Additionally, through bioinformatic analysis, biomarkers for predicting conversion to severe forms (total alopecia) were determined based on gene expression data in scalp biopsies, and a biomarker model according to the results of machine learning was constructed.

13 Conclusion

Artificial intelligence and machine learning (ML) are proving to be very beneficial in the diagnosis and treatment of autoimmune diseases, including systemic and organ-specific conditions like vitiligo and alopecia. With the help of AI, we can discover diseases earlier, anticipate how they will develop, evaluate how well a medication is working, and create more personalised treatment plans.

Despite the potential benefits of machine learning for precision medicine and improved patient outcomes in the management of autoimmune disorders, several issues remain. Data analysis including clinical, genetic, and imaging studies is where this becomes really apparent.

Early diagnosis and prognosis have both been greatly improved by ML. Imaging, laboratory, and hospital-related hazards and treatment outcomes While AI has not yet been widely used to treat organ-specific autoimmune illnesses, it has shown promise in improving diagnostic accuracy and guiding therapeutic options. Making artificial pancreas devices and anticipating when hypoglycaemia can happen are two examples of how artificial intelligence is being used to diabetes.

AI is revolutionising the field of gastroenterology by making it easier to diagnose and treat conditions including inflammatory bowel disease (IBD), coeliac disease, and gastric cancer. another example of the revolutionary capability of AI in healthcare, by analysing lesions to ascertain their severity and monitor the progression of diseases.

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