

ARTIFICIAL INTELLIGENCE (AI) AND CAPILLAROSCOPY: NEW HORIZONS

J. Doncheva-Dilova¹, N. Stoilov², V. Boyadzhieva²

¹UMHAT „Sv. Iv. Rilski“, Department of Occupational Diseases, Medical University – Sofia

²UMHAT „Sv. Iv. Rilski“, Department of Internal Diseases, Medical University – Sofia

Abstract. Nailfold capillaroscopy (NFC) is a well-established, highly specialized, non-invasive method for assessing microcirculation and represents the “gold standard” in rheumatology for distinguishing primary from secondary Raynaud’s phenomenon (RP). Through analysis of capillary structures in the nailfold region, clinicians can identify different patterns (scleroderma, scleroderma-like, and non-specific). Despite its clinical significance, image interpretation remains challenging due to subjectivity and the requirement for substantial examiner expertise. In recent years, artificial intelligence (AI) has offered novel solutions through the automated recognition and analysis of capillary structures. Machine learning and deep learning approaches have demonstrated high effectiveness in detecting abnormalities, classifying capillary patterns, and predicting the risk of systemic sclerosis. Projects such as CAPI-Detect, along with various other machine learning, deep learning, and neural network models (DenseNet-121, EfficientNet-B0, ResNet-34, NFC-Net), have shown that AI can identify novel quantitative parameters not accessible through traditional visual assessment and can increase the objectivity and reproducibility of results up to 90%. Most studies in this field focus on capillaroscopic patterns in systemic sclerosis (SSc); however, pilot studies in juvenile dermatomyositis, diabetes mellitus, and hypertension further highlight the applicability of these technologies. Some AI models are even capable of distinguishing onychomycosis, nail psoriasis, and subungual melanoma. Machine learning and deep learning models based on image analysis (Vision Transformer, ViT) appear to represent an additional valid system for the early and rapid interpretation of NFC images and morphological biomarkers in systemic sclerosis (SSc), integrating EULAR-validated algorithms for distinguishing scleroderma from non-scleroderma patterns with artificial intelligence (AI). Beyond its diagnostic applications, AI also holds potential in disease monitoring, assessment of therapeutic response, and the development of personalized treatment strategies. The processing of digital images through validated machine learning algorithms, neural networks, and related approaches is aligned with the priorities of the National Health Strategy 2030 for digitalization and the development of eHealth (Policy 2.5). The establishment of a National Digital Platform for Medical Diagnostics is envisaged, aimed at supporting all medical specialties. This platform will be integrated with the National Health Information System and the electronic patient record, with the primary objective of improving the quality of healthcare services. The integration of AI into medical practice opens new opportunities to support early diagnosis and improved management of patients with microangiopathy, facilitating timely detection and the prevention of complications, with the ultimate aim of ensuring better quality of life and preserved functional capacity.

Key words: Artificial Intelligence, machine learning, capillaroscopy

INTRODUCTION

Capillaroscopy as a Primary Diagnostic Method

Nailfold videocapillaroscopy (NVC) is an extremely useful, non-invasive, and reliable diagnostic method for analyzing microvascular changes in Raynaud’s phenomenon and various rheumatic diseases, as well as for assessing disease activity and prognosis [1-9]. Raynaud’s phenomenon (RP) is the most common clinical manifestation of microvascular involvement and represents a key feature of several systemic diseases, including systemic sclerosis (SSc), mixed connective tissue disease (MCTD),

systemic lupus erythematosus (SLE), dermatomyositis (DM), polymyositis (PM), and antiphospholipid syndrome (APS) [2-6].

The main capillaroscopic parameters evaluated include capillary density and morphology [10, 11], arrangement, capillary diameters (arterial limb, venous limb, and apical capillary loop) [10, 12]. The presence of dilated capillaries (arterial limb diameter > 15 µm or venous limb diameter > 20 µm) [13] and giant capillaries (diameter > 50 µm) [13, 14], avascular areas (distance between adjacent capillary loops greater than 500 µm in the distal row and greater than 300 µm in the proximal row), hemorrhages, and neoangiogenesis (newly formed vessels) is assessed [13].

In healthy individuals, the number of capillary loops ranges from 7 to 16 per millimeter, with the majority displaying a hairpin shape and a convex apical portion [13]. Hemorrhages may represent a manifestation of local trauma, in which case they are not associated with giant capillaries or neoangiogenesis. In cases of previous traumatic injury, isolated newly formed vessels (neoangiogenesis) may be observed, with preserved capillary density and normal capillary arrangement [10, 15]. The subpapillary plexus, from which nailfold capillaries originate, is visible in approximately 30% of healthy individuals [10, 11]. Variations in capillary morphology in healthy individuals include capillaries with tortuous limbs that do not intersect, as well as capillaries whose limbs cross at one or two points [8]. Definite signs of microangiopathy, which are not observed in healthy individuals, include giant capillaries and avascular areas, as well as neoangiogenesis in combination with reduced capillary density [10, 15, 16].

Video capillaroscopy is currently widely used in the differential diagnosis of primary and secondary Raynaud's phenomenon in rheumatic diseases [10-14]. The best-studied are the so-called "scleroderma" and "scleroderma-like" patterns. The "scleroderma" capillaroscopic pattern is characterized by the presence of giant capillaries, hemorrhages, disorganization of the capillary architecture, avascular areas, and neoangiogenesis. The early stage of "scleroderma-type" microangiopathy is characterized by the appearance of giant capillaries and isolated hemorrhages with preserved capillary arrangement and without avascular areas. In the so-called "active" phase, a large number of giant capillaries and hemorrhages are present, together with moderate capillary loss and architectural disorganization. In the "late" phase, extensive avascular areas and advanced architectural disorganization are observed, as well as numerous ramified capillaries, which represent neoangiogenesis [17, 18]. The "scleroderma-like" capillaroscopic pattern is observed in some patients with other systemic connective tissue diseases (undifferentiated connective tissue diseases, overlap syndromes, dermatomyositis, etc.) [10, 19, 20, 21, 22, 23].

Non-specific changes are observed mainly in patients with systemic lupus erythematosus, rheumatoid arthritis, and Sjögren's syndrome. These changes include the presence of dilated and elongated capillaries, a prominent subpapillary plexus, hemorrhages, and tortuous capillaries with altered morphology [10, 24, 25, 26, 27].

Application of artificial intelligence (AI) in medicine

Artificial intelligence (AI) refers to a field of computer science dedicated to the creation of systems capable of performing tasks that require human intelligence [28, 29].

AI uses a structured methodology to integrate external data, applying complex algorithms and generating predictions for specific scenarios [29, 30]. This systematic process involves advanced techniques, such as artificial neural networks and deep learning. The fundamental principles include data collection and preprocessing, model training, validation of results through cross-validation, selection of the optimal model and its integration into systems, such as desktop applications or embedded devices and hardware [29].

AI in healthcare involves the use of computational algorithms designed to analyze complex medical data (patient medical records, medical images, genomic sequences, etc.) in order to extract meaningful patterns, make predictions, and support healthcare professionals in clinical decision-making [28].

Different subfields of AI include:

a) **Machine learning (ML)** – enables AI systems to learn from large datasets without being explicitly programmed. [28] ML uses training datasets to extract correlations between variables and does not rely on predefined step-by-step processes [29].

b) **Deep learning networks (DLN)** – deep learning networks are inspired by the neural networks of the human brain. They are capable of analyzing tasks involving complex data representations and hierarchical feature learning [28]. This AI subfield has a broad scope and enables image-based diagnostics. Supervised learning focuses on establishing a relationship between inputs and desired outputs using provided input data and their corresponding correct outputs. The algorithm is trained by comparing its actual output with the correct outputs, allowing it to identify errors and making it useful for tasks such as classification and prediction [29].

c) **Natural language processing (NLP)** – natural language processing enables the extraction of information from medical texts or literature, as well as summarization and automation of medical coding [28, 29].

d) **Expert systems** – integrate domain-specific knowledge and logical reasoning to provide diagnostic support, treatment recommendations, and personalized health interventions based on established medical guidelines [28].

AI capabilities in capillaroscopic image analysis

Nailfold capillaroscopy (NFC) has both diagnostic and prognostic value, particularly in connective tissue diseases (especially systemic sclerosis) [28, 31, 32] and lifestyle-related diseases (including diabetes and arterial hypertension) [28, 33]. However, qualitative and quantitative analyses require high-quality NFC images and are time-consuming. Artificial intelligence has proven useful in overcoming these challenges [28, 31, 32, 33].

In recent years, artificial intelligence (AI) has offered new solutions through automated recognition and analysis of capillary structures. Machine learning and deep learning approaches demonstrate high effectiveness in detecting abnormalities, classifying capillary patterns, and predicting the risk of systemic sclerosis. Projects such as CAPI-Detect and various other machine learning, deep learning, and neural network models (DenseNet-121, EfficientNet-B0, ResNet-34, NFC-Net) can identify quantitative parameters and increase the objectivity and reproducibility of results up to 90%.

For the analysis of capillaroscopic images, **three main types** of models are primarily used:

- **Object detection models**, which localize blood capillaries within the image. These models determine the number of capillaries and their spatial distribution and can also detect the presence of hemorrhages.

- **Image classification models**, which classify images according to capillary morphology.

- **Keypoint detection models**, which enable measurement of the diameters of the arterial limb, venous limb, and apical capillary loop [34].

Capillary.io is a web-based platform for automated capillaroscopic analysis. The system improves the image interpretation process, saves time, and instantly calculates parameters when all required data are available. It should be noted that no AI system is perfect and can operate with 100% accuracy. Therefore, physicians have the option to correct inaccurate predictions generated by the AI model. Nevertheless, the platform is useful for result interpretation, as image quality may vary depending on the operator's skills and the microscope used [35].

The platform has been developed based on two major projects – CAPI-SCORE and CAPI-DETECT.

CAPI-SCORE [35] is a quantitative algorithm that automatically classifies nailfold videocapillaroscopy (NVC) patterns in patients with scleroderma or systemic diseases. Its main objective is to overcome the subjectivity associated with manual assessment by capillaroscopists. A total of 1,040 capillaroscopic

examinations from patients in nine Spanish and Colombian hospitals were collected. The total number of analyzed images was 25,798 and the total number of capillaries assessed manually was 310,277. Consensus was achieved in 912 of the 1,040 cases. Of these, 851 were selected as the “gold standard” for software analysis after prior manual evaluation by three experienced capillaroscopists according to the EULAR criteria for normal, nonspecific, SSc-early, SSc-active, and SSc-late patterns. The algorithm uses quantitative metrics (capillary density [capillaries/mm]; percentage of abnormal capillaries [irregular morphology]; percentage of giant capillaries; tortuosity; microhemorrhages). The CAPI-SCORE is based on the EULAR “fast track” algorithm. The variables assessed by the software include capillary density and the percentage of giant capillaries, hemorrhages, tortuosities and abnormal capillaries, the latter defined as ramified, bushy, or coiled capillaries, often originating from a single normal capillary. The results show an accuracy of approximately 0.88 in distinguishing scleroderma from non-scleroderma patterns; approximately 0.82 in classifying early, active, and late phases; and approximately 0.73 in differentiating between “normal” and “non-specific” patterns. When the analysis was restricted to NVC examinations for which full consensus among investigators was achieved, the algorithm's accuracy improved. The authors emphasize the need for larger, multicenter cohorts for future validation, as well as potential integration with machine learning (ML) methods to further enhance accuracy and clinical applicability [35].

CAPI-DETECT represents the next step in the development of automated systems for the study of capillaroscopic images, facilitating the identification and classification of abnormalities [36]. Deep learning-based software (ML), trained on more than 2,500 manually annotated images, was used and an algorithm (CAPI-DETECT) was developed to distinguish three models: SSc versus non-SSc patterns; a model for classifying SSc into early, active and late phases according to Cutolo's classification and normal versus non-specific patterns. Capillaroscopic images were prevalidated by comparing the algorithm's predictions with annotations obtained by consensus of three or more of five trained capillaroscopists on images from more than 1,000 patients with RP. The algorithm aims to achieve accuracy comparable to that of an experienced capillaroscopist and to support routine clinical practice in determining capillaroscopic patterns based on quantitative metrics. Capillaroscopic images were obtained from patients with

SSc or RP in nine Spanish and U.S. hospitals. A total of 1,724 capillaroscopic examinations (from patients with RP or SSc) were randomly and blindly analyzed by three to four trained capillaroscopists. Capillaroscopies with partial (1,490) and complete (515) consensus were used to train machine learning-based classification models using CatBoost software, incorporating 24 variables related to capillary architecture extracted through automated analysis of NVC images. A total of 298 capillaroscopic examinations (20% of all cases) were randomly selected as a validation set (i.e., not used for model training but intended for assessment of the validity of the final models). CAPI-DETECT achieves an accuracy of 0.973 for distinguishing SSc from non-SSc patterns, 0.934 for differentiating SSc patterns (early, active, and late phases), and 0.837 for distinguishing normal from non-specific patterns. The authors also report an improvement in the overall accuracy of CAPI-DETECT compared with CAPI-SCORE, particularly in the classification of normal versus non-specific patterns. Gema M. Lledó-Ibáñez et al. [36] indicate that one of the key advantages of CAPI-DETECT is its ability to support physicians by saving time and providing probabilistic and unbiased assessments specific to each pattern, based on quantitative analysis of capillary structure, shape, size and density. As a limitation, the authors note that model training was based on subjectively classified capillaroscopic images and that the clinical significance of nonspecific non-SSc patterns remains uncertain [36].

Other similar models for the interpretation of capillaroscopic images using AI based on machine learning and deep learning have been developed worldwide.

An international group of authors (Omar Emam et al. [37]) conducted a literature review aimed at systematically summarizing all studies that used artificial intelligence algorithms for the analysis of capillaroscopic images. Several databases (PubMed [including MEDLINE], EMBASE, CINAHL, and Web of Science) were searched using keywords such as “artificial intelligence,” “machine learning,” “deep learning,” and “nailfold capillaroscopy.” A total of 105 studies were identified, but only 10 were included and analyzed based on predefined exclusion criteria. In 8 of the 10 studies, supervised deep learning was the primary methodological approach and the most frequently investigated disease was systemic sclerosis (6/10 studies). The datasets varied considerably, ranging from 50 images obtained from 50 participants to 17,126 images from 289 participants. Only two of the reported algorithms demonstrated

not only diagnostic, but also prognostic value. AI shows significant potential to support (or automate) the analysis of nailfold capillaroscopic images by providing a tool to assist diagnosis and, in some cases, prognosis. Across all studies, precision and accuracy improved following prior manual annotation. The authors emphasize that current research is heterogeneous in terms of study design, sample size and labeling methodology and that large multicenter validation studies are lacking and are necessary before this approach can be routinely implemented in clinical practice [37].

The largest number of studies have been conducted in the field of rheumatology, particularly in systemic sclerosis (SSc) [31, 35-39], although some studies have also reported the application of AI in the interpretation of capillaroscopic images in patients with dermatomyositis [40], arterial hypertension and diabetes mellitus [37], as well as in the field of dermatology for the diagnosis of nail diseases, such as onychomycosis, nail psoriasis, subungual melanoma [28].

Garaïman et al. [31] evaluated the effectiveness and reliability of a transformer-based deep learning model for visual recognition (ViT) as an off-the-shelf solution for identifying specific microangiopathic features in capillaroscopic images from patients with SSc. The ViT analysis was compared with the assessments of practicing rheumatologists. The selected evaluation parameters included dilated capillaries, giant capillaries, capillary loss, microhemorrhages, and the presence of a scleroderma pattern. A total of 17,126 capillaroscopic images from 234 patients from the EUSTAR cohort and 55 patients from the VEDOSS cohort were analyzed. The results demonstrated up to 84.5% accuracy of the AI model in image interpretation. According to the authors, ViT is a well-performing and easily accessible tool for assessing microangiopathy patterns on NFC images and can support rheumatologists. However, final diagnosis still requires the judgment of an experienced capillaroscopist [31].

Ebadi Jalal et al. [38] developed and evaluated an automated deep learning (DL) model for detecting abnormal capillaroscopic images using a neural network (EfficientNet-B0) and cascade transfer learning [38]. A total of 288 capillaroscopic images were collected from 225 participants at a hospital in Tijuana, Mexico. Three internists sorted and labeled the images as normal (16 images, 6%) or pathological (272 images, 94%). Only one image per participant was obtained, taken from a single finger (the index finger). The base architecture for the training model was EfficientNet-B0, pre-trained

on ImageNet. Cascade transfer learning was applied – first using domain-specific classes (e.g., dermatomyositis, tortuosity) (Dataset A), followed by fine-tuning for the target task of normal versus pathological classification (Dataset B). According to the authors, this cascade transfer learning model achieved “perfect” results in terms of accuracy, precision, and other performance metrics, likely due to the small size of the test dataset. For future research, the authors recommend validation on larger and more diverse datasets, as well as expansion of the task toward classification of different types of pathologies rather than only normal versus pathological categories [38].

Lutfi Ozturk et al. [39] investigated how AI (based on machine learning and deep learning) can analyze nailfold capillaroscopy images for diagnosis and classification in systemic sclerosis and related conditions within the French prospective multicenter observational SCLEROCAP study. Images from 100 patients with SSc were analyzed. After initial manual assessment by experienced capillaroscopists, the images were divided into a training set (70%) and a validation set (30%). For deep learning, three pre-trained models from the TIMM library (ResNet-18, DenseNet-121, and VGG-16) were tested on raw NC images. With machine learning, performance ranged from 0.60 to 0.73 for each variable. Using deep learning, a minimum accuracy of 0.87 was achieved, with the DenseNet-121 model providing the best results. The authors recommend validation of the model in larger cohorts [39].

One study reports the potential of artificial intelligence (AI) to distinguish children with juvenile dermatomyositis (JDM) from healthy controls based on the analysis of capillaroscopic images (Kassani et al. [40]). A total of 1,120 images from 111 children with active JDM (diagnosed between 1990 and 2020) and 321 images from 31 healthy controls were used. A deep learning neural model (NFC-Net) was trained to discriminate between JDM cases and controls and to predict disease activity (active versus inactive). The NFC-Net model demonstrated high performance in distinguishing JDM from healthy controls, with accuracy = 0.91, sensitivity = 0.85, specificity = 0.90, precision = 0.95, and AUROC = 0.93. For predicting disease activity (active vs. inactive), performance was more moderate (AUROC = 0.75; accuracy = 0.74). The authors emphasize the need for larger, prospective and more diverse cohorts to validate the model's applicability in clinical practice [40].

A Polish pilot study aimed to validate software for automated capillary counting and classification of nailfold capillaroscopy images as “normal” or “patho-

logical.” [41]. A total of 200 capillaroscopic images were used – 100 from patients with systemic sclerosis or scleroderma-spectrum disorders and 100 from healthy individuals (controls). Each image was manually analyzed and described using dedicated software. An artificial intelligence model for capillary classification and counting was applied and validated through cross-validation. ResNet-34 (a deep residual neural network) was used for the classification task (normal vs. pathological). For the capillary counting task, the YOLOv3/Darknet algorithm was employed for object detection of capillaries. The evaluation parameters included sensitivity, specificity, and precision of capillary counting. Results obtained from neural network training were compared with those from manual analysis. The sensitivity of the automated tool relative to manual assessment for classification of normal and pathological images was 89.0% and specificity was 89.4% in the training group; during validation, sensitivity and specificity were 89.0% and 86.9%, respectively. According to the authors, the software may serve as a useful tool for rapid classification of normal and altered capillaroscopic patterns, regardless of the examiner's level of experience. As an additional advantage, the authors note that the model is not limited to distinguishing SSc alone. The ability to rapidly analyze large numbers of capillaroscopic images and obtain detailed quantitative results may expand research into other diseases as well [41].

Bulgaria's National Health Strategy 2030 also envisages digital transformation in the healthcare sector, based on the development of wireless communication networks (4G/5G), cloud technologies, and the implementation of high-speed optical data transmission networks [42].

By 2030, the establishment of a National Digital Platform for Medical Diagnostics is envisaged. The aim is to encompass digital imaging diagnostics across all medical specialties and to enable the creation of a database of digital images and their secondary processing using validated machine learning (ML) algorithms, neural networks and other AI-based methods. This platform will be integrated with the National Health Information System (NHIS) and the electronic patient record. The National Digital Platform for Medical Diagnostics will be intended for all healthcare domains, with particular emphasis on oncology, diagnostic radiology, pathology and others [42].

CONCLUSION

The application of AI offers novel solutions and supports the analysis of capillaroscopic images, par-

ticularly for medical professionals with less experience in this field. Despite the increasing integration of AI into medicine, the use of various AI models is not yet part of routine clinical practice due to limited and heterogeneous datasets, variability among studies, small cohort sizes and a predominant focus on specific patterns and diseases (primarily the “scleroderma” pattern and SSc). Currently available algorithms demonstrate high accuracy in distinguishing SSc (including its subtypes) and scleroderma-like patterns, although accuracy for differentiating “normal” versus “nonspecific” patterns remains relatively lower. The sensitivity and specificity of automated tools for classifying normal and pathological images improve significantly when combined with manual assessment by an experienced capillaroscopist.

In the future, validation of AI models on larger and more diverse datasets is recommended, along with expansion of tasks toward classification of different types of pathologies, not only normal versus pathological. Integration of AI into medical practice may facilitate early diagnosis, prevent complications and ensure better quality of life and work capacity for patients with microangiopathy.

Библиография / References

1. Дончева-Дилова Ж., Бояджиева Вл., Стоилов Н., Кунева Т. Капиляроскопията като метод за диагностика на микроваскуларни нарушения при системни заболявания, синдром на Рейно и вибрационна болест, Ревматол, 2021, 29, (2).
2. Souza EJ, Kayser C. Capilaroscopia periungueal: relevância para a prática reumatológica [Nailfold capillaroscopy: relevance to the practice of rheumatology]. *Rev Bras Reumatol*. 2015 May-Jun;55(3):264-71. Portuguese. doi: 10.1016/j.rbr.2014.09.003.
3. Cutolo M, Sulli A, Secchi ME, Pizzorni C. Kapillarmikroskopie und rheumatische Erkrankungen: State of the art [Capillaroscopy and rheumatic diseases: state of the art]. *Z Rheumatol*. 2006 Jul;65(4):290-6. German. doi: 10.1007/s00393-006-0071-2.
4. Cutolo M, et al. Nailfold capillaroscopy is useful for the diagnosis and follow-up of autoimmune rheumatic diseases. A future tool for the analysis of microvascular heart involvement? *Rheumatology* 45 Suppl 4 (2006): iv43-6.
5. Ocampo-Garza SS, Villarreal-Alarcón MA, Villarreal-Treviño AV, Ocampo-Candiani J. Capilaroscopia: una herramienta diagnóstica valiosa. *Actas Dermosifiliogr*. 2019;110:347–352.
6. Wu PC, Huang MN, Kuo YM et al. Clinical applicability of quantitative nailfold capillaroscopy in differential diagnosis of connective tissue diseases with Raynaud's phenomenon. *J Formos Med Assoc*. 2013 Aug;112(8):482-8. doi: 10.1016/j.jfma.2012.02.029.
7. Hysa E, Pizzorni C, Sammorì S et al. Microvascular damage in autoimmune connective tissue diseases: a capillaroscopic analysis from 20 years of experience in a EULAR training and research referral centre for imaging. *RMD Open*. 2023 Jul;9(3):e003071. doi: 10.1136/rmdopen-2023-003071.
8. Rodriguez-Reyna TS, Martín Nares E, Bermudez-Bermejo P, et al. Zamora-Legoff V, Hernandez-Molina G. Increased Frequency of Nailfold Videocapillaroscopy Abnormalities in Primary antiphospholipid (PAPS) Patients [abstract]. *Arthritis Rheumatol*. 2017; 69 (suppl 10). <https://acrabstracts.org/abstract/increased-frequency-of-nailfold-videocapillaroscopy-abnormalities-in-primaryantiphospholipid-paps-patients/>. Accessed: December 12, 2023.
9. Ferrari G, Gotelli E, Paolino S, et al. Antiphospholipid antibodies and anticoagulant therapy: capillaroscopic findings. *Arthritis Res Ther*. 2021 Jun 27;23(1):175. doi: 10.1186/s13075-021-02551-6.
10. Ламбова С, Бояджиева Вл. Капиляроскопия в ревматологията – консенсус на Българското дружество по ревматология.
11. Bollinger, A, Fagrell. B. Clinical capillaroscopy – a guide to its use in clinical research and practice. Hogrefe & Huber Publishers Toronto, (1990).
12. Lambova, S. N. Nailfold capillaroscopy – practical implications for rheumatology practice. *Curr Rheumatol Rev*, (2020) 16(2), 79–83.
13. Schmidt, J. A., Caspary, L., von Bierbrauer, A., et al. Standardisierung der Nagelfalz-Kapillarmikroskopie in der Routinediagnostik. (1997), 26(1), 5–10.
14. Sander, O., Sunderkötter, C., Kötter, I et al. Capillaroscopy. Procedure and nomenclature. *Z Rheumatol*, (2010), 69(3), 253-262.
15. Lambova, S., Mueller-Ladner, U. Nailfold capillaroscopy of fingers and toes – variations of normal. *Curr Rheumatol Rev*, (2017) 13, 28–35.
16. Hoerth C, Kundi M, Katzenschlager R, Hirschl M. Qualitative and quantitative assessment of nailfold capillaries by capillaroscopy in healthy volunteers. *Vasa*, (2012) 41(1), 19–26.
17. Cutolo M, Sulli A, Pizzorni C, Accardo S. Nailfold videocapillaroscopy assessment of microvascular damage in systemic sclerosis. *J Rheumatol*, (2000) 27(1), 155–160.
18. Cutolo M., Sulli, A., Smith, V. How to perform and interpret capillaroscopy. *Best Practice and Research: Clin Rheumatol*, (2013) 27(2), 237–248.
19. Maricq, H. R., Le Roy, E. C. Patterns of finger capillary abnormalities in connective tissue disease by “wide-field” microscopy. *Arthritis Rheum*, (1973) 16(5), 619–628.
20. Maricq, H. R., LeRoy, E. C., D'Angelo, W. A., et al. Diagnostic potential of in vivo capillary microscopy in scleroderma and related disorders. *Arthritis Rheum*, (1980) 23(2), 183–189.
21. Maricq, H. R., Harper, F. E., Khan, M. M., et al. Microvascular abnormalities as possible predictors of disease subsets in Raynaud phenomenon and early connective tissue disease. *Clin Exp Rheumatol*, (1983) 1(3), 195–205.
22. Cutolo, M. Atlas of capillaroscopy in rheumatic diseases (1st ed.). Elsevier, (2010).
23. Cutolo M., Paolino S., Smith, V. Nailfold capillaroscopy in rheumatology: ready for the daily use but with care in terminology. *Clin Rheumatol*, (2019) 38(9), 2293–2297.
24. Smith, V., Herrick, A. L., Ingegnoli, F et al. Standardisation of nailfold capillaroscopy for the assessment of patients with Raynaud's phenomenon and systemic sclerosis. *Autoimmun Rev*, (2020) 19(3), 102458.
25. Lambova, S. N., Mueller-Ladner, U. Capillaroscopic pattern in systemic lupus erythematosus and undifferentiated con-

- nective tissue disease: What we still have to learn? *Rheumatol Int*, (2013) 33(3), 689–695.
26. Lambova, S. N., Hermann, W, Müller-Ladner, U. Comparison of qualitative and quantitative analysis of capillaroscopic findings in patients with rheumatic diseases. *Rheumatol Int*, (2012) 32(12), 3729–3735.
 27. Lambova, S. N, Mueller-Ladner, U. Capillaroscopic pattern in inflammatory arthritis. *Microvasc Res*, (2012) 83(3), 318–322.
 28. Gaurav V, Grover C, Tyagi M, Saurabh S. Artificial Intelligence in Diagnosis and Management of Nail Disorders: A Narrative Review. *Indian Dermatol Online J*. 2024 Dec 11;16(1):40-49. doi: 10.4103/idoj.idoj_460_24.
 29. Bekbolatova M, Mayer J, Ong CW, Toma M. Transformative potential of AI in healthcare: Definitions, applications, and navigating the ethical landscape and public perspectives. *Healthcare (Basel)* 2024;12:125.
 30. Toma, M, Concu, R. Computational Biology: A New Frontier in Applied Biology. *Biology* 2021, 10, 374
 31. Garaiman A, Nooralahzadeh F, Mihai C, Gonzalez NP, Gkikopoulos N, Becker MO, et al. Vision transformer assisting rheumatologists in screening for capillaroscopy changes in systemic sclerosis: an artificial intelligence model. *Rheumatology (Oxford)* 2023;62:2492–500.
 32. Nitkunanantharajah S, Haedicke K, Moore TB et al. Three-dimensional optoacoustic imaging of nailfold capillaries in systemic sclerosis and its potential for disease differentiation using deep learning. *Sci Rep* 2020;10:16444.
 33. Shah R, Petch J, Nelson W, et al. Nailfold capillaroscopy and deep learning in diabetes. *J Diabetes* 2023;15:145–51.
 34. Capillary.io. Applying artificial intelligence in capillaroscopy to improve diagnosis of systemic autoimmune diseases. <https://en.capillary.io/posts/capillaroscopy-autoimmune-diseases/>
 35. Capillary.io.: Precision capillaroscopy powered by AI. <https://en.capillary.io/>
 36. del Carmelo Gracia Tello B, Luis Sáez Comet L, Gema Lledó G, et al. Capi-score: a quantitative algorithm for identifying disease patterns in nailfold videocapillaroscopy, *Rheumatology*, Volume 63, Issue 12, December 2024, Pages 3315–3321, <https://doi.org/10.1093/rheumatology/keae197>
 37. Omar S, Emam OS, Ebadi Jalal M et al. Artificial Intelligence Algorithms in Nailfold Capillaroscopy Image Analysis: A Systematic Review. Hive AI Innovation Studio, University of Louisville, Louisville, Kentucky, US. Artificial Intelligence Algorithms in Nailfold Capillaroscopy Image Analysis: A Systematic Review
 38. Ebadi Jalal, M., Emam, O.S., Castillo-Olea, C, et al. Abnormality detection in nailfold capillary images using deep learning with EfficientNet and cascade transfer learning. *Sci Rep* 15, 2068 (2025). <https://doi.org/10.1038/s41598-025-85277-8>
 39. Lutfi Ozturk L, Charlotte Laclau Ch, Carine Boulon C, et al. Analysis of nailfold capillaroscopy images with artificial intelligence: Data from literature and performance of machine learning and deep learning from images acquired in the SCLEROCAP study, *Microvascular Research*, Volume 157, 2025, 104753, <https://doi.org/10.1016/j.mvr.2024.104753>. (<https://www.sciencedirect.com/science/article/pii/S002628622400102X>)
 40. Kassani, P.H., Ehwerhemuepha, L., Martin-King, C, et al. Artificial intelligence for nailfold capillaroscopy analyses – a proof of concept application in juvenile dermatomyositis. *Pediatr Res* 95, 981–987 (2024). <https://doi.org/10.1038/s41390-023-02894-7>
 41. Brzezińska OE, Rychlicki-Kicior KA, Makowska JS. Automatic assessment of nailfold capillaroscopy software: a pilot study. *Rheumatology*. 2024;62(5):346-350. doi:10.5114/reum/194040.
 42. Министерски съвет, портал за обществени консултации. Стратегически документи. Национална здравна стратегия 2030. <https://strategy.bg/StrategicDocuments/View.aspx?Id=1604>

Постъпил за печат: 17.10.2025 г.

Submitted: 17.10.2025

✉ **Адрес за кореспонденция:**

Ас. д-р Жаклин Дончева-Дилова
Катедра по професионални болести
УМБАЛ "Св. Иван Рилски" ЕАД
Медицински университет – София
ул. „Урвич“ № 13
София 1431
тел.: +359 888953636
e-mail: <mailto:j.doncheva-dilova@medfac.mu-sofia.bg>
j.doncheva-dilova@medfac.mu-sofia.bg

✉ **Correspondence address:**

Assis. Dr. Jaklin Doncheva-Dilova
Department of Occupational Diseases
University Hospital "Sv. Iv. Rilski"
Medical University – Sofia
13 Urvich str.
BG – 1431 Sofia
tel: +359 888953636
e-mail: <mailto:j.doncheva-dilova@medfac.mu-sofia.bg>
j.doncheva-dilova@medfac.mu-sofia.bg