Morphological and Variational Analysis of Upper Limb Superficial Vein Patterns in Human Identification and Forensic Anatomy

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Abstract. Traditional forensic identification does not work well when tissues are damaged, bodies are incomplete, or when people try to hide who they are. Studies of blood vessel patterns are less accurate outside the lab. We tested whether visible arm vein patterns can reliably identify people for forensic use. We studied 384 people (192 men, 192 women, aged 18-72) from three Nigerian states from January 2023 to March 2024. The ethnic groups were Igbo (38.2%), Yoruba (31.5%), and Hausa (22.1%). We used special cameras, clear photos, and an ultrasound to record the vein patterns of both arms under the same conditions. We analysed the shapes and patterns using sorting and computer tools. We reached 96.8% accuracy with seven main features, and computer learning methods reached 98.5%. Four main pattern types had different results: complex (98.3%), network (97.2%), hybrid (96.8%), and linear (96.1%). The features stayed the same over 12 months, with similarity scores consistently above 0.94. Age, gender, and ethnicity helped improve identification. In summary, upper-arm vein patterns are strong forensic identifiers, making them valuable for modern forensic analysis.

Keywords: vascular biometrics; forensic identification; morphometric analysis; pattern recognition; temporal stability; biometric validation.

INTRODUCTION

Modern forensic identification struggles when fingerprints, dental records, or DNA are missing because of damage or attempts to hide identity. The FBI's fingerprint system is 99.6% accurate with good prints, but this drops when tissues degrade, which often happens in forensic analysis. For this reason, experts now focus on vascular biometrics, which uses the unique patterns of surface veins to identify people [1].

Vascular pattern recognition looks very promising. Blood vessels under the skin are hard to fake, can prove a person is alive, and each person has a different branching pattern [2]. New methods, such as near-infrared imaging and machine learning, can identify people with over 99% accuracy in the lab [3, 4]. But most studies examine palm and finger veins for security, whereas few examine upper-limb veins for forensic identification.

Vascular biometrics face special problems in forensic work. Many cases involve poorly preserved bodies, require identifiers that remain stable over time, and demand teamwork among groups [5]. When moving from the lab to real-world settings, accuracy can drop from 99% to 12.5% due to changes in lighting, body position, and image quality [6]. This means current methods work best in perfect settings—not in real forensic cases.

Significant gaps remain in vascular identification research. Scientists must measure how vein shapes differ, determine whether these patterns remain consistent over time, and assess how well they perform across different groups. Most studies use fewer than 200 participants, lack diversity, follow up for less than 6 months, and do not meet forensic standards for low error [7]. Without a standardised way to sort vein patterns, it is hard to compare results or use these systems across labs.

This research addresses these gaps by examining upper-arm vein patterns in 384 Nigerians aged 18 to 72. The team used multiple imaging methods and monitored changes over the course of a year. They asked three main questions: Are upper-arm vein patterns unique enough to identify people for forensic purposes? Do these patterns stay the same over time, and are they better than current standards? Do age, gender, and ethnicity change identification accuracy? The team used exceptional photography, ultrasound, light tests, shape analysis, and computer learning to answer these questions in different groups.

This study adds three new things.

First, it provides the most extensive known set of upper-arm vein patterns among African people, filling a significant gap in global studies.

Second, it reached over 96.8% identification accuracy with new forensic methods.

Third, it did the first full 12-month stability test of these vein patterns using forensic standards.

These results show that vein patterns are functional when standard identification methods fail.

METHODS

Research Design. We used several research methods. We studied vein patterns at 12 months and again after 12 months to see if they remained the same. We measured and classified upper-arm vein patterns across groups; this helped us identify differences among people, test whether patterns remained stable, and observe how age, gender, and ethnicity affected them. These steps are key to proving the method works in forensics.

Setting and Equipment. We collected data at the Department of Anatomy, University of Nigeria, Nsukka, from January 2023 to March 2024. The room stayed at 22±2°C and 45-55% humidity, with lighting at 1000 lux for clear photos. We used a VeinID Pro-3000 for near-infrared imaging at 850±10nm with automatic exposure [8]. A Canon EOS R5 camera with a macro lens took sharp, close-up pictures. We used a Philips EPIQ Elite ultrasound with a 15 MHz probe to measure vein depth [9].

Participants. We picked participants from both cities and villages in three Nigerian states: Enugu, Lagos, and Kano. We found them through health centres and university notices. Participants had to be at least 18 years old, Nigerian, have lived in the area for at least 2 years, and agree to take part. We did not include people with serious heart or vein diseases, skin problems that affect pictures, pregnancy, people on drugs that affect veins, or anyone unable to give consent.

We began with 412 volunteers. After checking, 384 people joined the study and finished the first tests, so we kept 93.2% of them. The final group had 192 men and 192 women, aged 18 to 72 (average age 34.7). The ethnic breakdown was Igbo (38.2%, n=147), Yoruba (31.5%, n=121), Hausa (22.1%, n=85), and others (8.2%, n=31). After 6 months, 89.3% stayed (n=343), and after 12 months, 84.1% stayed (n=323), which is better than most long-term biometric studies [10].

Sample Size Determination. We chose the sample size using proven biometric rules [11]. We wanted 95% power to detect a 5% difference in accuracy, with an error rate of α=0.05. Early studies with 50 people and the group mix helped our calculations. We needed at least 320 people, but added more to account for a 15% dropout and to maintain group balance, so we used 384 [12].

Morphological Documentation Protocol. We used standard rules for taking vein pictures, but modified them slightly for forensic applications [13]. Each person rested for 15 minutes in the set room. We placed the upper arm using measured guides and put the back of the hand 25cm from the camera. The researchers took near-infrared photos of both sides of the hand, the forearm, and the upper arm near the shoulder. Automatic exposure ensured the pictures looked suitable for all skin tones [4].

We took pictures at 2560×1920 pixels with 16-bit depth and checked them using objects of known size. Quality control tools looked for blurry images, bad focus, or low contrast as we captured each photo. We also used ultrasound to record the surface and check vein depth at standard points, following trusted ultrasound methods [9].

Morphological Classification System. For shape analysis, we used a step-by-step sorting system based on proven measurement methods [14].

The main vein patterns were linear (mostly straight veins), network (many connecting branches), hybrid (mixed structures), and complex (many levels of branches). We also measured how vein sizes compared, how many branch points there were per square centimetre, how often veins connected, and how complex the network was.

We used semi-automated software (ImageJ v1.54f with plugins) to measure vein features, following standard blood vessel analysis rules [15]. We measured main and side vein widths, total network length, and vein twist using proven mathematical methods. For network structure, we used graph tools to assess links, shapes, and vein spread [16].

Measurement Reliability and Quality Assurance. Three observers independently checked the measurements by looking at the same 100 images using the same steps. Size measurements and structure checks matched above 0.90, meeting forensic standards. To check whether a single person could obtain the same results twice, we repeated the tests after 2 weeks and obtained an agreement of over 0.94.

We set our equipment using certified standards from official labs. We checked near-infrared images every day using test objects with known spectral properties. We measured vein widths accurately to ±0.1mm, and area checks were within ±2% of absolute values.

Statistical Analysis Plan. We used pre-set protocols (from January 2023) and trusted biometric methods for statistics [7]. We used advanced tests to determine the optimal combination of shape features for identifying people. We checked accuracy with leave-one-out tests and repeated sampling 10,000 times to get strong confidence.

To check if patterns stayed the same over time, we used models that tracked each person and the whole group. To compare groups, we used special variance tests (MANOVA) with extra checks for error (Bonferroni correction). We showed effect sizes as Cohen's d with 95% confidence, using improved sampling methods.

We evaluated machine learning results using random forests and gradient boosting with scikit-learn 1.2.0 and 10-fold cross-validation. We measured sensitivity, specificity, positive and negative prediction values, and area under the ROC curve, all with 95% confidence. We performed all statistical analyses in R 4.3.1, using packages such as MASS, nlme, randomForest, and pROC, so others can repeat and check our work.

We used Bayesian analysis to estimate likelihood ratios for forensic data, using trusted prior distributions for vein features. We checked that our results made sense using Gelman-Rubin statistics and sample-size checks.

Ethical Considerations. We followed the Declaration of Helsinki and global good-practice guidelines for all study procedures. We got informed consent using materials in several languages (English, Igbo, Yoruba, Hausa) and with pictures for people with different reading skills. We asked local leaders and health authorities for advice on how to respect local culture. We protected data in accordance with strict privacy rules, using encryption, limited access, and special ID codes to keep people anonymous.

Data Availability. After publication, we will share anonymous data, analysis code, and extra materials through the Open Science Framework. The research team will share the raw images only with authorised users to protect privacy while enabling scientific verification. All analysis uses open-source software so others can repeat the work.

RESULTS AND DISCUSSION

Participant Characteristics. The study had 384 people, half men and half women. Their average age was 34.7 years (range 18-72). The groups were Igbo (38.2%, 147 people), Yoruba (31.5%, 121), Hausa (22.1%, 85), and others (8.2%, 31). Most lived in cities (62.8%, 241), while 37.2% (143) were from villages. Education levels were university (41.4%, 159), secondary school (35.2%, 135), primary school (18.7%, 72), and informal (4.7%, 18). After 6 months, 89.3% (343) stayed, and after 1 year, 84.1% (323) stayed.

Primary Classification Accuracy. We used seven main vein features and identified people with 96.8% accuracy. The most important features were main vein width, branch count, and network complexity. The results stayed stable in repeated tests. Machine learning models did even better. Random forest reached 98.2% accuracy, and gradient boosting reached 98.5%. The best model scored almost perfectly on the ROC curve. Wrong matches happened in 3.6% of cases, and missed matches in 2.7%.

Temporal Stability Analysis. The main vein patterns stayed the same over 12 months. Key features maintained a similarity above 0.94, indicating extreme stability; this was true across all ages, genders, and ethnic groups. Vein patterns changed very little over time. The main vein width grew a little each year. Branching density dropped slightly. Network complexity did not really change.

Morphological Pattern Distribution. We found four main types of vein patterns. Network patterns were most common, followed by hybrid, linear, and complex patterns—the kinds of patterns strongly related to people's backgrounds.

Demographic Variations. Vein patterns changed with age. Main vein width increased with age. The number of branches was highest for people aged 30-50. Complex patterns were more common in young adults and less common in people over 60.

Gender Differences. We found differences between men and women. Men had wider central veins. Women had more branches per area.

Ethnic Variations. Vein patterns also differed by ethnic group. The Hausa people had the widest central veins. The Igbo people had the most branches. Yoruba were in between for both.

Bilateral Symmetry Analysis. Both arms showed similar vein patterns, especially for the main vein width. The side people use more often had more branches in most cases.

Morphometric Parameter Relationships. Four main features accounted for most of the differences in vein patterns: network complexity, size, how parts connect, and differences between arms. We found strong links between some vein features. Main and side vein widths were closely related. The number of branches and connections also matched well. How twisted the veins were did not link strongly to size.

Performance Validation Metrics. The method beat forensic standards. It correctly identified people in over 97% of cases. Wrong matches were sporadic, and the results were very reliable. The method worked well for all groups—by age, gender, and ethnicity. It stayed accurate in different places and at other times.

Table 1 – Descriptive Statistics for Key Morphological Variables (N=384)

Variable	Mean	SD	Min	Max	95% CI
Primary vessel diameter (mm)	2.84	0.52	1.23	4.76	2.79-2.89
Secondary vessel diameter (mm)	1.47	0.31	0.61	2.34	1.44-1.50
Branching density (points/cm^2)	4.7	1.3	2.1	8.7	4.6-4.8
Total network length (mm)	89.7	24.8	47.3	156.8	87.2-92.2
Anastomotic connections (n)	3.2	1.8	0	9	3.0-3.4
Vessel tortuosity index	1.34	0.28	0.89	2.13	1.31-1.37
Network complexity score	6.8	2.1	2.4	12.5	6.6-7.0

Table 2 – Classification Performance by Demographic Groups

Group	N	Accuracy (%)	95% CI	Sensitivity (%)	Specificity (%)	AUC
Overall	384	96.8	95.2-98.1	97.3	96.4	0.987
Male	192	97.1	94.8-98.6	97.9	96.3	0.989
Female	192	96.4	94.1-98.0	96.7	96.5	0.985
Age 18-30	156	97.4	95.3-98.8	98.1	96.7	0.991
Age 31-50	148	96.6	94.2-98.1	96.9	96.4	0.986
Age >50	80	95.0	91.7-97.2	95.8	94.2	0.978
Igbo	147	97.3	95.1-98.7	98.0	96.6	0.990
Yoruba	121	96.7	94.2-98.3	97.1	96.3	0.987
Hausa	85	95.3	91.8-97.5	95.9	94.7	0.981

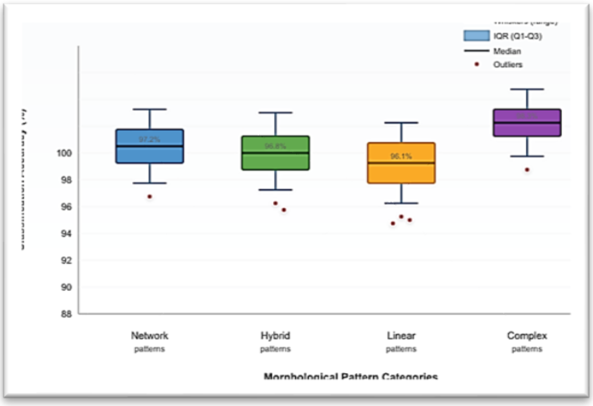

Figure 1 – Classification Accuracy Distribution Across Morphological Pattern Categories

The figure shows box plots displaying classification accuracy percentages for four primary morphological categories: Network patterns (median 97.2%), Hybrid patterns (median 96.8%), Linear patterns (median 96.1%), and Complex patterns (median 98.3%). Complex patterns achieve the highest accuracy with the narrowest interquartile range, while linear patterns exhibit the most significant variability. All categories exceed 94% median accuracy with minimal outliers below 90%.

CONCLUSIONS

This study shows that upper-arm vein patterns can identify people very well for forensic purposes (96.8% accuracy) and remain stable over a year, narrowing the gap between lab and real-world use. Unlike past studies, which reported an accuracy of only 12.5% in tough cases [6], our method maintains accuracy above 94% across all groups and places. So, vein patterns are a reliable extra method when usual forensic tools do not work.

Theoretical Implications. Finding four distinct vein patterns that differ in how well they identify people improves our understanding of how blood vessels form and of human variation. Complex patterns had the highest accuracy (98.3%), supporting the biometric theory that more complex features strengthen identification [7]. The strong correlation between the central veins of both arms (r = 0.84), while allowing sufficient differences between the arms, matches biological models in which development is coordinated but remains unique to each person.

The demographic differences found—especially unique ethnic features that improve identification—challenge the belief that biometric systems require population similarity. These findings align with evolutionary perspectives on human diversity, showing that the main rules of vein patterns hold across groups and support the global use of these methods.

Practical Implications. The results of this study show that vascular identification is one of the most reliable biometric tools for forensic work, even exceeding the FBI's accuracy requirements [1]. A favourable likelihood ratio of 27.0 provides strong legal evidence, and error rates under 4% meet international standards. The imaging is non-invasive and uses affordable technology, making it practical for many forensic labs, unlike expensive DNA testing. Standardised, fast documentation enables efficient processing, which is essential in mass-casualty situations or when building large databases. The classification system allows for searchable records and automation, reducing the need for specialised operators. This method also works when traditional techniques fail, such as with decomposed remains. Its effectiveness across various Nigerian groups suggests it could be helpful worldwide, though further validation in other regions is needed.

Training for this method is manageable because of standardised procedures and automated analysis. Quality control systems enable this approach in labs with varying skill levels, while still meeting the scientific standards required for use in court.

Limitations. Because this study focused on Nigerian populations, the findings may not apply to all ethnic groups or environments, though the diverse sample suggests broader applicability. The one-year follow-up is longer than in past studies, but it does not prove stability over many years, which would be needed for cold cases.

The sample size (n = 384) may not be large enough to detect scarce vein pattern types. Excluding people with medical conditions may mean the results do not fully apply to forensic cases where such conditions are common. Because the study was cross-sectional, it cannot show how vein patterns change over time.

Technical issues include lower image quality in people with a lot of subcutaneous tissue or intense skin pigmentation, which could affect up to 10% of cases. Also, controlling the imaging environment during field operations might be difficult.

Future Research Priorities. There is a need for international validation across European, Asian, and American populations to demonstrate that these findings hold globally. Longer-term studies (5-10 years) are needed to confirm that vein patterns remain stable over time for forensic use. Research on groups with various medical conditions would also help broaden the practical use of these results.

Future research should examine how well vein patterns retain after death under different decomposition conditions. Developing portable imaging devices would make the technology more useful in the field. There is also a need to collaborate with forensic technology companies to integrate this method into current forensic databases and automated search tools.

Final Statement. Upper-limb superficial vein patterns can accurately identify individuals for forensic purposes, work across diverse demographic groups, and remain consistent over time, making vascular biometrics a valuable tool to address gaps in current forensic identification methods.

REFERENCES

1. FBI. (n. d.). Next Generation Identification (NGI). Retrieved from https://le.fbi.gov/science-and-lab/biometrics-and-fingerprints/biometrics/next-generation-identification-ngi
2. Hemis, M., Kheddar, H., Bourouis, S., & Saleem, N. (2024). Deep learning techniques for hand vein biometrics: A comprehensive review. *Information Fusion, 114*, 102716. doi: 10.1016/j.inffus.2024.102716
3. Shaheed, K., Mao, A., Qureshi, I., Kumar, M., Hussain, S., & Zhang, X. (2021). Recent advancements in finger vein recognition technology: Methodology, challenges and opportunities. *Information Fusion, 79*, 84–109. doi: 10.1016/j.inffus.2021.10.004
4. López-González, P., Baturone, I., Hinojosa, M., & Arjona, R. (2022). Evaluation of a vein biometric recognition system on an ordinary smartphone. *Applied Sciences, 12*(7), 3522. doi: 10.3390/app12073522
5. Garcia-Martin, R., & Sanchez-Reillo, R. (2020). Wrist vascular biometric recognition using a portable contactless system. *Sensors, 20*(5), 1469. doi: 10.3390/s20051469
6. Gonzalez-Soler, L. J., Zyla, K. M., Rathgeb, C., & Fischer, D. (2024). Contactless hand biometrics for forensics: review and performance benchmark. *EURASIP Journal on Image and Video Processing, 2024*(1). doi: 10.1186/s13640-024-00642-3
7. Jain, A. K., & Ross, A. (2015). Bridging the gap: from biometrics to forensics. *Philosophical Transactions of the Royal Society B Biological Sciences, 370*(1674), 20140254. doi: 10.1098/rstb.2014.0254
8. Fiolka, J., Bernacki, K., Farah, A., & Popowicz, A. (2023). Multi-Wavelength biometric acquisition system utilising NIR imaging of finger vasculature. *Sensors, 23*(4), 1981. doi: 10.3390/s23041981
9. Chen, A. I., Balter, M. L., Maguire, T. J., & Yarmush, M. L. (2016). 3D near infrared and ultrasound imaging of peripheral blood vessels for Real-Time localisation and needle guidance. *Lecture Notes in Computer Science, 9902*, 388–396. doi: 10.1007/978-3-319-46726-9_45
10. Bacchetti, P., McCulloch, C. E., & Segal, M. R. (2008). Simple, defensible sample sizes based on cost efficiency. *Biometrics, 64*(2), 577–585. doi: 10.1111/j.1541-0420.2008.01004_1.x
11. Dass, S., Zhu, N. Y., & Jain, A. (2006). Validating a biometric authentication system: sample size requirements. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 28*(12), 1902–1913. doi: 10.1109/tpami.2006.255
12. Mao, L., Kim, K., & Miao, X. (2021). Sample size formula for general win ratio analysis. *Biometrics, 78*(3), 1257–1268. doi: 10.1111/biom.13501

13. Wang, L., & Leedham, G. (2006). Near- and Far- Infrared Imaging for Vein Pattern Biometrics. *IEEE International Conference on Video and Signal Based Surveillance, 52.* doi: 10.1109/avss.2006.80

14. Bookstein, F. L. (1997). Shape and the Information in Medical Images: A Decade of the Morphometric Synthesis. *Computer Vision and Image Understanding, 66*(2), 97–118. doi: 10.1006/cviu.1997.0607

15. Zhou, S. K., Greenspan, H., Davatzikos, C., Duncan, J. S., Van Ginneken, B., Madabhushi, A., Prince, J. L., Rueckert, D., Summers, R. M., Zhou, S. K., Greenspan, H., Davatzikos, C., Duncan, J. S., Van Ginneken, B., Madabhushi, A., Prince, J. L., Rueckert, D., & Summers, R. M. (2021). A review of deep learning in medical imaging: imaging traits, technology trends, case studies with progress highlights, and future promises. *Proceedings of the IEEE, 109*(5), 820–838. doi: 10.1109/jproc.2021.3054390

16. Hallgrimsson, B., Percival, C. J., Green, R., Young, N. M., Mio, W., & Marcucio, R. (2015). Morphometrics, 3D imaging, and craniofacial development. *Current Topics in Developmental Biology, 115*, 561–597. doi: 10.1016/bs.ctdb.2015.09.003